EX ANTE FORECASTING OF UNCERTAIN AND IRREVERSIBLE DAIRY INVESTMENTS: IMPLICATIONS FOR ENVIRONMENTAL COMPLIANCE

By

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Dedicated to my Uncle Jack

in loving memory

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Uncertainty about costs and requirements for environmental compliance is an important determinant of dairy producers' investment behavior. *Ex ante* forecasting of how uncertainty and irreversibility are likely to affect producers' responsiveness to agricultural technologies has implications for the design of environmental policies.

Previous research on adoption behavior focused on short-run input substitution options, and yielded *ex post* descriptions of who adopted technologies and why. This research offers two extensions: first, its focus is a technology adoption decision involving irreversible investments rather than input substitution. Second, *ex ante* forecasting ranks alternative strategies for policy design, rather than prescribing modifications after observed adoption behavior failed to correspond with policy objectives.

Economic theory on investment under irreversibility and uncertainty suggests that people tend to postpone investment when payoffs are uncertain, when information unfolds gradually and when sunk costs of investing are high. Under rapid technological change, the decision is not whether to invest now or never but rather whether to invest now or later. Optimal investment timing is when the value of investing exceeds the value of waiting. The more uncertain an investment, the higher the value of waiting. This research is the first known application of this theory to agricultural technology adoption.

Empirical analysis focused on Texas dairy producers' propensity to adopt free stall dairy housing technology. Free stall investments offer both productivity-enhancement and pollution-abatement advantages.

The research was conducted in three stages. First, anticipated costs and returns were profiled, and the present value of the investment was positive. Second, results from simulation modeling were reported, with milk production and feed costs as stochastic variables. Incorporating risk, the expected returns from investing offset the investment cost only 61 percent of the time. Finally, simulation methods were used to assess how uncertainty and irreversibility affects optimal investment behavior.

Accounting for uncertainty more than doubled the rate of return required to trigger investment, compared with the no-risk assessment. Adding a stochastic component in the cost of complying with environmental rules further increased the required trigger rate. Uncertainty about environmental compliance requirements adversely affects the rate of technology adoption.

CHAPTER 1
INTRODUCTION

In 1910 over 35 percent of Americans lived and worked on farms (McConnell and Brue, 1990). Agriculture then was viewed as an engine for economic growth and vitality, "as the solution to many of the nation's problems" (Batie, 1988, p. 1). Things have changed: increasingly, agriculture is viewed as contributing to society's problems, particularly environmental problems. One force behind this trend is fewer, larger farms producing more food and fiber on less land. In addition, a declining proportion of American families live on farms, less than two percent in 1987 (McConnell and Brue, 1990). "Commercial agriculture is increasingly perceived as comprised of a few 'factory-like' farms which neither need nor deserve special societal-funded benefits and exemptions from societal rules" (Batie, 1988, p. 1).

Both city dwellers and rural residents lament the decline of what they remember as "family farming" (Strange, 1988; Comstock, 1987). Where commercial agriculture is thriving, however, concern about the demise of the family farm is often overwhelmed by complaints against large-scale farm enterprises (Sims, 1993; Brown, 1993), often best characterized as NIMBY (not in my back yard). Neighbors worry about surface water damages and groundwater contamination, as well as barnyard odors. When large farms are seen as polluters, public sympathy is sparse.

Until the mid-1980s, agriculture was outside the purview of environmental policy. During the 1970s and the early 1980s, the focus of environmental policy was industrial pollution abatement, especially hazardous waste clean-up and toxic emissions control (Brimelow and Spencer, 1992; Landy et al., 1990). Foundations for federal water policy were built in the Federal Water Pollution Control Act of 1972 (P.L. 92-500) and the Clean Water Act of 1977 (P.L. 95-217), legislation which targeted point source pollution but which also laid the groundwork for nonpoint source water pollution control (Carriker, 1979; Whittlesey and Carriker, 1993).[1]

The first step in preventing water pollution from nonpoint sources has been to define the problem. Under Section 319 of the Clean Water Act, each state was required to conduct a nonpoint source assessment and then to develop a state water management plan. From their involvement with state-level planning and assessment efforts, as well as in the coordination of watershed-level education and demonstration projects, the federal Environmental Protection Agency (EPA) concluded that "agriculture continues to be the single largest contributor to nonpoint source problems in the nation. It is the leading source of impacts to rivers, lakes and wetlands" (USEPA, 1992a, p. 2).

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[1]A point source of pollution is one which can be attributed to a particular source; the legal definition is "a discernable, confined, and discrete conveyance" (Libby and Boggess, 1990). Some livestock activities, confined irrigation return flows, and greenhouse facilities have characteristics of point sources.

Most agricultural activities are categorized as nonpoint source pollution: "it arises from numerous sources and it is virtually impossible to link any particular source to downstream damages" (Phipps and Crosson, 1986). Cropland, rangeland, and pasture are considered nonpoint sources of pollution.

The farm policy agenda included environmental issues *per se* beginning in the mid-1980s. After fifty years of sponsoring voluntary, cost-shared soil conservation (Batie, 1983), agricultural pollution was still muddying surface waters. Clark et al. (1985) estimated the net social damage cost of soil erosion-related water pollution at $6.1 billion. Water quality goals were implicit in the conservation provisions of the 1985 Food Security Act (Title XIII of P.L. 99-198) through programs and rules which built on soil conservation efforts already in place (Kovan et al., 1987) and through new policy initiatives like the Conservation Reserve Program, where water quality protection was one of several objectives (Reichelderfer and Boggess, 1988). In the 1990 Food, Agriculture, Conservation and Trade Act (P.L. 101-624), water quality goals were made explicit. For example, under the Water Quality Initiative Program, farmers were offered easements on cropland prone to water quality damages.

Better Information on Agricultural Nonpoint Pollution

Since 1985, significant resources have been committed to research, education, and technical assistance, in order to improve upon existing sound science relating to agriculture and the environment, as well as to broaden what is known about the performance of on-farm pollution abatement systems and grassroots technology-transfer strategies. In 1990 the Congressional Office of Technology Assessment (OTA) set the tone for these activities. To "build the knowledge base to support informed decision making" (OTA, 1990, p. 18) was a key recommendation from their report on the risk of groundwater contamination from agricultural nonpoint pollution.

When former President Bush launched his Water Quality Initiative, an official statement from the U.S. Department of Agriculture (USDA) recognized that "much remains unknown about the magnitude and the extent of agriculture's effects on water quality, the specific nature of agricultural chemical fate and transport in water systems, and the economic and environmental tradeoffs among alternative production management systems" (USDA, 1989, p. 7). Accordingly, a major thrust of the implementation of the Presidential Water Quality Initiative was scientific research, along with on-farm evaluations of pollution control technologies.

The EPA has played an increasingly important role in developing and implementing environmental policies pertaining to agriculture. They coordinated nonpoint source assessment and planning at the state level, as mandated under Section 319 of the Clean Water Act (USEPA, 1992a). In 1992 the EPA sponsored a symposium to facilitate analysis and an exchange of ideas concerning "lessons learned from a ten-year experiment in controlling nonpoint source pollution" (USEPA, 1992b, p. iii). The Rural Clean Water Program (RCWP) was administered jointly by federal, state, and local agencies from 1980 to 1990. There were 21 pilot projects in agricultural watersheds in 22 different states. Education and technical assistance were the primary emphasis of the RCWP.

The cumulative result of the RCWP pilot projects, the EPA's Section 319 programming, and the USDA's Water Quality Initiative is an increase in the depth and the breadth of collective knowledge about nonpoint pollution from agriculture and its control. This enhanced understanding of nonpoint pollution from agriculture is

instrumental in setting policy priorities. Strategies for managing nonpoint pollution problems are emerging, but the challenge of deciding who is responsible and who should pay is perpetual. The majority of the EPA's regulatory experience with pollution abatement has involved point sources rather than nonpoint sources. With point source pollution, it is relatively easy to link cause and effect and to establish pollution control requirements. Building on their experience with industrial point-source pollution control, the EPA has targeted two agricultural quasi-point sources as policy priorities: irrigation tailwater and large livestock operations (USEPA, 1992a).

Livestock Waste Management Framed as a Key Issue

In accord with the 1972 Clean Water Act, the EPA has authority to regulate concentrated animal feeding operations (CAFOs) as point sources under the National Pollution Discharge Elimination System (NPDES) general permit.[2] Any livestock operation with more than 1000 animal units[3] (700 dairy cows) is required to comply with the NPDES permit, as must any CAFO smaller than 1000 animal units if there is a non-zero probability of them discharging into the waters of the United States.

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[2]Regulations pertaining to point source polluters--including CAFOs--are outlined in Title 40, Chapter 1, Subchapter D, Part 122 of the Code of Federal Regulations (40:122:CFR). Specifically, the NPDES general permit specifies structural guidelines for a CAFO waste management system. The basic requirement is sufficient water storage capacity to accommodate all runoff from the CAFO, up to the rainfall from a 24-hour, 25-year storm event.

Thirty-four states have been delegated authority to administer the NPDES permit. In Texas, New Mexico, Oklahoma, and Louisiana (EPA Region VI), NPDES permits are administered by EPA ("National ...", 1993; see Outlaw, et al., 1993).

[3]An animal unit is defined as a feeder steer ("National ...", 1992).

The conclusions of a report to Congress on nonpoint pollution management spotlighted water quality damages associated with livestock as a policy priority. "Improper manure storage and utilization can contaminate water, ... (W)aterbodies and groundwater resources near livestock operations are endangered" (USEPA, 1992a, p. 187). The report suggested promotion of best management practices and implementation of permit requirements for (CAFOs) as potential solutions to livestock waste management problems. Others have echoed EPA's point of view. "Animal manure management, including containment and land application, appear to be major components of water quality issues," (Porterfield, 1993, p. 22). This position was articulated by a coalition of all state farm bureaus, joined by several commodity associations and agribusinesses, and organized by the American Farm Bureau Federation. The policy statement was released in response to a final review of the RCWP pilot projects (USEPA, 1992a).

General consensus is emerging that livestock waste management is an urgent policy issue; and, in response, significant information on the topic has been gathered. Dialogue on a wide range of livestock waste management issues was encouraged through a national workshop entitled "National Livestock, Poultry and Aquaculture Waste Management" (Blake et al., 1992), sponsored jointly by the USDA and the EPA. Four of 21 RCWP pilot projects focused on dairy waste management. From these pilot projects, comparative analysis on the performance of alternative technologies and practices designed to improve the effectiveness of dairy waste management was developed, based on scientific studies in Okeechobee, Florida

(Gunsalus et al., 1992), Lancaster County, Pennsylvania (Koerkle, 1992; Hall and Risser, 1992), St. Albans Bay, Vermont (Meals, 1992; Schlagel, 1992), and Tillamook Bay, Oregon (Moore et al., 1992).

Informed Policy Design

From the research, education, and technical assistance programs conducted during the 1980s and early 1990s, there has been progress in setting an agenda for reducing agricultural pollution. Much has been learned about causes of agricultural nonpoint pollution and about effective strategies for pollution abatement. Yet substantial uncertainty exists about the performance of pollution abatement technologies, about the cost-effectiveness of alternative technologies, and about appropriate policy instruments to promote technology adoption. Economic theory suggests that people tend to postpone irreversible investments when uncertainty is important and when additional information is anticipated. This applies to investments aimed at pollution abatement, as well as to adoption of other technologies.

Problem Statement

This study tests the general hypothesis that uncertainty about the costs and requirements associated with environmental compliance are important determinants of dairy producers' investment behavior. The corollary is that improved understanding of the impact of uncertainty on technology adoption behavior can be used to inform the design and implementation of environmental policies.

Dairy producers view uncertainty and inadequate information as disincentives to technology adoption. The problem was summarized by a spokesman for the Texas Association of Dairymen: "we've got to stop this moving-target business in terms of permitting. Every time you get close to the goal line, the goal line moves back another 30 yards" (Krapf, 1992b). The empirical thrust of this research is to develop a methodology for *ex ante* forecasting of investment behavior, taking into account the effect of environmental compliance. Evolving compliance requirements send mixed signals to producers, and thus can cause discrepancies between intentions and results.

Research Objectives

1. To use a theoretical model of investment under irreversibility and uncertainty to develop an empirical methodology for *ex ante* forecasting of investment behavior, and to specify hypotheses about the effects on investment of changing the discount rate and changing uncertainty.

2. To apply this empirical *ex ante* forecasting model to analyze the likely investment behavior of dairy producers in central Texas, and to test hypotheses about the responsiveness of their investment behavior to changes in the discount rate and changes in uncertainty.

3. To discuss implications for policy design and implementation drawn from this *ex ante* forecasting of dairy investment behavior.

A Focus on Dairy Waste Management

The focus of this economic analysis is a case study of investments in dairy housing facilities with potential for both enhancing the technical efficiency of milk production as well as improving the reliability of dairy waste management systems in central Texas. Three factors played a role in this choice.

Policy Discussions on Livestock Waste Management

One reason for spotlighting dairy manure management was its immediate policy relevance. The EPA has an interest in fine-tuning the design and implementation of its policies toward CAFOs. Congressional discussions on the re-authorization of the Clean Water Act are scheduled for 1993, and livestock waste management--including an emphasis on permitting small concentrated animal feeding operations--has been named as an item on the re-authorization agenda (Outlaw et al., 1993; Malik et al., 1992; Hosemann, 1992). Water quality is also considered an important policy issue for the 1995 farm bill (Carriker, 1993).

Compliance on Dairies Requires Major Investments

A second reason to study dairy waste management is that the sizeable investments required for dairies to comply with environmental rules makes compliance a fundamentally different economic decision than efforts to satisfy mandatory pollution control requirements on crop farms. In Okeechobee, Florida, investments in environmental compliance have raised the cost of producing milk by

$1.10 per hundredweight (Boggess et al., 1992).[4] Texas dairy producers paid fixed costs of approximately $184 per cow to construct waste management systems on large dairies, and the annual operating expenses associated with environmental compliance in Texas are estimated at $75 per cow (Lovell et al., 1992). These investments and operating expenses have implications for dairy profitability, as well as for economic viability. Regional discrepancies in the costs of environmental compliance influence which parts of the country have a comparative advantage in producing milk.

Livestock waste management requires large investments, whereas pollution abatement on crop farms is achieved largely through input substitution.[5] Decisions involving large investments bring to bear fundamentally different economic behavioral assumptions than do input substitution decisions. Thus, an appropriate conceptual framework for analyzing investment behavior differs from the paradigm for predicting technology adoption involving input substitution.

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[4]This estimate is based on an amortization of investment and management costs over the life of the dairy production system.

[5]For example, soil erosion, groundwater contamination from pesticides or fertilizer, or water quality damages from irrigation can often be handled with input substitution--such as changing tillage practices, trying a new pesticide, or optimizing the timing of fertilizer or irrigation applications. For example, if one herbicide is banned, then a farmer can try a different herbicide without buying new equipment and without changing other aspects of the cropping system. If the change proves unsatisfactory, it is easy to switch back. Sunk costs associated with this experimentation are minimal.

In contrast, investments in livestock waste management systems are irreversible. Irreversibility means that the value-in-use of waste management systems is greater than their salvage value. Financial payoffs from adopting waste management technologies are unlikely to completely to offset the sunk investment costs.

Rapid Technological Change in Dairy Waste Management

The third reason for an interest in dairy waste management investments is that choosing an optimal economic strategy for dairy pollution control is conditioned by rapid technological change. The cutting edge is a moving target. Jointness between dairy waste management systems and milk production technologies makes a difference; appropriate technology choice requires taking account of the synergy between what is good for pollution abatement and what is good for milk production. "Separate analysis of dairy and waste disposal costs can lead to a sub-optimal decision since the waste disposal method utilized must be compatible with dairy housing" (Matulich et al., 1977, p. iii), according to an empirical study of technical efficiency levels (economies of size) in large-scale dairying.

Evidence from the Florida experience highlights the potential economic benefits from investments in environmental compliance which also improve production efficiency on dairies (Boggess et al., 1992). Pressure to comply with environmental regulations played a role in the accelerated adoption of technologies designed to control pollution which, at the same time, improve production efficiency on dairies. Florida's Dairy Rule, one of the earliest and most stringent state environmental regulations pertaining to agriculture, was passed in 1987. To meet a 1991 deadline, the 49 dairy producers in the Lake Okeechobee drainage basin had two options. They could either install prescribed technologies and best management practices to contain runoff from their dairy facilities and pastures, or they could sell permanent easements on their dairy property to the Florida Department of Environmental Regulation.

Thirty dairies stayed in production in the Okeechobee basin after 1991. In addition to investments to satisfy minimal Dairy Rule technology requirements, several Okeechobee producers opted to install technologies with components above and beyond those required (Boggess et al., 1992). For example, in conjunction with compliance-driven construction projects, some producers built roofed structures covering the cows' feeding areas. These modifications in dairy housing were designed to avert heat stress, thus improving cow comfort. Enhanced efficiency from these dairy investments translated into higher milk production, and higher revenues from milk sales helped to offset the cost of the investments. On average, dairy producers who installed no optional components spent 37 percent less than those who invested in systems with extra amenities (respectively, investments of $434 per cow versus $593 per cow). Florida producers who invested in optional components, however, reaped benefits: their investment costs have been offset by increases in revenues due to improved milk production averaging $136 per cow per year. In contrast, increases in revenues of $12 per cow per year were realized by dairies which installed only the minimal technologies required under the Dairy Rule.

In summary, technologies with potential both to enhance pollution abatement and to promote higher milk production are an important option for dairy producers who feel urgent pressure to comply with environmental rules and, at the same time, worry about how to pay for their pollution abatement efforts. Those concerned about designing policies to promote adoption of cost-effective technologies, therefore, also have a stake in a comprehensive assessment of the likelihood of beneficial synergies

associated with modifications in dairy housing, as well as the financial risks associated with investments in such technologies.

A Case Study in Central Texas

Erath County is the top milk-producing county in Texas, its production in 1992 was over a billion pounds of milk (Texas Milk Market Administrator, 1993). County milk production from Erath County ranked twelfth nationwide in 1991 (USDA, 1992). The dairy industry in Erath County has grown rapidly: over the past ten years, county milk sales have more than doubled, reaching $144 million in 1991 (Krapf, 1992). Milk production capacity continues to expand: production in Erath County increased 14.25 percent between May, 1992 and May, 1993 (Texas Milk Market Administrator, 1993).

Rapid growth in the dairy industry has spawned local controversy concerning groundwater protection, surface water quality and nuisance odor complaints. Local environmentalists, the Cross Timbers Concerned Citizens, called for a moratorium on new dairies in Erath County and surrounding counties in April, 1992 (Brown, 1992). Since 1989, the Texas Water Commission (TWC) has required permits for all dairies with over 250 cows (31 Texas Administrative Code, 321.34). Recently, TWC visited all dairies in Erath County--their "Dairy Outreach" program--to monitor the operation and management of dairy waste management systems (Foster, 1993). The EPA considers dairy regulations which now apply in Texas among the most stringent in the United States ("National ...", 1993, p. 7615). Erath County dairy producers have

made and are making major investments in environmental compliance, both personal and financial (DeJong, 1993a; Cordell, 1992; Stalcup, 1992; Terrell, 1992).

Erath County, Texas, is a fascinating laboratory for studying technology adoption. Its dynamic economic and environmental setting is an opportunity to observe dairy producers' investment decision making in response to environmental regulations. As experience with compliance accumulates, this baseline data from Texas will facilitate comparative analysis of the technology adoption processes in Texas and Florida. In the meantime, observations from Florida[6] suggested a focus for this study of technology adoption on investments in free stall dairy housing.

A Description of Free Stall Dairying

Free stall dairying originated in the Pacific Northwest in the 1960s and is common on large dairies in the Midwest (Pagano et al., 1992a). A tiny but growing minority of dairy producers in the South have adopted free stall technology recently (Pagano et al., 1992b, 1992c, 1993a, 1993b). Before 1992, only one of 193 dairies in Erath County, Texas, was a free stall facility. Two free stall barns were built in Erath County in 1992, and other Texas dairy producers were considering either building free stall barns or investing in other housing modifications (Hallady, 1992b).

[6]Previous economic research in Florida documented that two of 30 dairy producers opted to build free stall facilities in response to the Dairy Rule (Boggess et al., 1991). Outside the Okeechobee area, a few Florida producers have built free stall facilities and others are considering it. Free stall barns were among the dairy housing modifications debated by a panel of Florida dairy producers in January, 1993: "What We Built, How it Works, and What We'd Build Now" (Pagano et al., 1993b) during a workshop organized by producers.

Free stall facilities are roofed dairy housing units. Cows housed in free stalls spend 80 to 90 percent of their time indoors, under covered loafing and feeding areas. Free stall facilities are well ventilated, so that cows stay cool and comfortable. Free stall barns feature a clean, private space where each cow can lie down. Stalls are designed so that cows can enter and exit them easily, so that cows can lie down and rise without struggling, without getting muddy or dirty. Because of enhanced cow comfort in free stalls, cows tend to spend more time eating than do cows on open lots (Albright and Timmons, 1984). The more comfortable the cows, the more they eat and the more milk they produce.

Compared with the open lot housing used on most dairies in the South, the major environmental advantages from free stall dairying are smaller corrals (less runoff to catch), and approximately 90 percent of the manure being handled in a flush system which uses recycled water (Pagano, et al., 1993b). Cows deposit almost all manure adjacent to feeding areas. In a free stall facility, therefore, most manure is handled under roof, whereas feeding areas on open lot facilities are subject to runoff. Many free stall facilities are equipped with solid separators to remove manure solids collected in the flush system before the waste water is stored or recycled.[7] On many free stall facilities in Texas, recycled solids are used as free stall bedding, which reduces the volume and the costs of off-farm manure disposal and reduces

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[7]Waste water from free stall facilities is often rich in nutrients, thus irrigation rates are often lower than on open lot dairies. Often, free stall dairies require more land for waste management than do open lot dairies. Proper water storage and irrigation on a free stall dairy requires a high level of management.

environmental risks (water quality damages, nuisance odor) associated with land application of manure (Pagano et al., 1992b). Consumptive use of water on free stall facilities is generally less than on open lot facilities.

Scientific evidence on pollution abatement performance from free stall facilities is sparse and often anecdotal (Pagano et al., 1992a, 1993b). No comprehensive scientific and/or economic comparisons exist of the benefits and costs--environmental and financial--of building and managing a free stall facility, versus a conventional open lot facility, versus dairy housing with covered feeding areas only (no free stalls).

Producers' Opinions on Free Stall Dairy Investments

In Florida and Texas, a minority of dairy producers view investing in a free stall facility as the best way to satisfy the current environmental regulations, as reflected by low adoption rates (Pagano et al. 1992b, 1993a). A larger number of producers are instead building facilities with covered feeding areas only (Pagano et al., 1993b). In focus group discussions and personal interviews (Pagano et al., 1993b), dairy producers have mentioned their reluctance to take on the financial risk associated with making any large capital investment in the face of uncertainty about future environmental requirements, as well as uncertainty about future milk prices, as factors in their decision making about whether and when to modify their dairy facilities. Some dairy producers, moreover, have expressed concern about environmental regulators advocating free stall technology before thorough scientific and economic analysis of all technology options has been undertaken.

This research is not intended to promote the adoption of free stall technology but rather to analyze the economic implications of its adoption and to develop a methodology for analyzing free stall technology as well as other dairy waste management technologies. The research presented in this thesis, on *ex ante* forecasting of investments in free stall dairy facilities, will supply one of the components required for comparative analysis of technology options for dairy waste management. Contingent on management and site-specific environmental conditions, free stall facilities are one of several possible cost-effective technologies for improving the reliability of dairy waste management systems in central Texas, as well as for improving milk production efficiency.

In summary, the objective of this economic analysis is an *ex ante* assessment of dairy producers' responsiveness to free stall technology in central Texas. Decision making about dairy housing investments is a dynamic problem set, and the economic analysis presented in this thesis is framed as an experiment with the theoretical and methodological problem of *ex ante* forecasting of adoption behavior. This is a departure from the existing economic paradigm for modeling the adoption and diffusion of agricultural technology. Conventional economic analysis focuses on *ex post* analysis using cross-sectional time series data. *Ex ante* forecasting of adoption behavior may prove useful in policy design and implementation.

Outline of the Dissertation

The second chapter, "Literature Review," describes the foundations on which the research presented in this dissertation is built. Important ideas from behavioral economics theory and from the previous empirical research on technology adoption literature are overviewed.

The third chapter, "Theory," presents the theory of investment under irreversibility and uncertainty, introduced with a description of its underpinnings in option pricing theory. The chapter concludes with a list of research hypotheses.

The fourth chapter, "Data and Methods," develops a methodology for empirical testing of the research hypotheses. A profile of the costs and returns associated with free stall dairying is presented. These empirical data are analyzed to assess whether and when dairy producers are likely to invest in a technology with potential to both improve production efficiency and the reliability of dairy waste management.

The fifth chapter, "Results," describes formal tests of five research hypotheses and an interpretation of the results.

The final chapter discusses the policy implications of the research and outlines suggestions for further research.

CHAPTER 2
LITERATURE REVIEW

The theme of this research is economic behavior under complexity. Two sets of ideas are melded to support a conceptual framework for *ex ante* forecasting of investment behavior under irreversibility and uncertainty: ideas from behavioral economics and from empirical research on technology adoption.

Agricultural production is risky and complex. Farmers seek to adopt technologies which promise either to reduce risk or to increase efficiency or both. The extent to which the benefits from adoption are expected to outweigh the costs makes a difference. Due to uncertainty about the consequences of doing things a new way, the decision whether and when to adopt a technology is often itself a complex process. Why producers adopt new agricultural technologies, which technologies they adopt, and how quickly have been important questions for applied economic analysis. A computerized search of the Journal of Economic Literature and the Index of Economic Articles (1969 - 1990) listed 4783 entries under the key word "innovation." Searching for the term "adoption" generated a list of 272 references, and there were 394 articles on "diffusion." Rogers and Thomas (1975) catalogued 1800 empirical studies on the diffusion of innovations. A review article on adoption of agricultural innovations in developing countries listed 133 references (Feder et al., 1985).

Technological progress in agriculture is the product of a series of individual decisions and actions taken by innovative producers. Choices about technology adoption are complex, and are usually made with incomplete information. *Ex ante*, it is impossible to predict with certainty whether a new technology will pay off or whether it will streamline operations on the farm. Generally speaking, analysis of decision making and, specifically, analysis of choices regarding allocation of scarce resources--including time (Schultz, 1975) and attention (Simon, 1978)--are the domain of behavioral economics.[1] Though no single, unified theory or methodology of behavioral economics has yet been synthesized (Caldwell, 1986), insights relevant to modeling adoption of agricultural technologies are implicit in the conceptual frameworks developed by behavioral economists, as well as in their case studies of decision making under complexity.

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[1]This description of Herbert Simon's life work describes well the scope of behavioral economics:

> To construct a comprehensive framework for modeling and analyzing the behavior of man and his organizations faced with a complex environment, recognizing the limitation of his ability to comprehend, describe, analyze and to act, while allowing for his ability to learn and to adapt (Ando).

This precis was written to commemorate Simon being honored with the 1978 Nobel Laureate in Economics. The award caused consternation among several leading economists who considered Simon a heretic (Cicarelli and Cicarelli, 1989). Simon has chosen to describe himself as a behavioral scientist, rather than as an economist. He deliberately sets himself apart from a profession which he has accused of "ignoring the real world when it contradicts the theory" (Simon, p. 379, 1989a). Behavioral economics has yet to find its niche in the mainstream of the discipline of economics.

This chapter is divided into two parts. First, there is a discussion of concepts from behavioral economics, and of its underpinnings in psychology theory. The second topic is a description of empirical research on technology adoption.

Concepts from Behavioral Economics

"The quest to understand decision making as it really is" (Cicarelli and Cicarelli, 1989, p. 265) through empirical analysis--by observing and scrutinizing how people actually make decisions--is the central issue in behavioral economics. Ideas and methods from behavioral economics add a potentially valuable dimension to the existing paradigm for modeling economic choices about technology adoption. Optimization is the behavioral mechanism at the heart of conventional economic models, and predictive power is the standard criterion for evaluating economic models (Friedman, 1953). What distinguishes behavioral economic analysis is a concern for the descriptive power, as well as the predictive power, of models.

Simon explained why there is friction between description and prediction in economic modeling: "an understanding of mechanisms does not guarantee predictability" (Simon, 1989b, p. 100). According to the two-edged Occam's Razor criterion for evaluating economic theories, it is best to "accept the simplest theory that works, . . . [to select] theories that make no more assumptions than necessary to account for the phenomena" (Simon, 1979, p. 495). Consistent with this maxim, the behavioral assumptions underpinning standard optimization models are prized for their succinctness. On the other hand, these profit-maximizing and cost-minimizing

assumptions attribute heroic performance to the human cognitive system, as if the first-best option were always seen and taken. This is the tradeoff implicit in Occam's Razor: parsimonious predictive models may not accurately depict how real-world decisions are made. "Hence, ... the two edges of the razor cut both ways" (Simon, 1979, p. 495). The dilemma is to design economic models where the economic behavior being represented corresponds more closely with observable behavior, without either the sacrificing predictive power or the parsimony of models.

Neither a thorough overview of behavioral economics nor prescriptions on how to combine concepts from behavioral economics with conventional techniques for analysis are attempted in this literature review. Rather, the purpose of the first half of this chapter is to relate three sets of ideas which played key roles in the design of this research. First, reliability theory (Heiner, 1983) and its underpinnings in signal detection theory (Green and Swets, 1966) are described. Then the theory of bounded rationality and the satisficing as a mode of behavior (Simon, 1979) are discussed.

Reliability as the Origin of Predictable Behavior

Heiner (1983, 1985, 1988) postulated that uncertainty is the source of predictable behavior, and that adhering to tried-and-true decision rules is a natural response to uncertainty. When faced with new opportunities, people are inclined to fall back on rule-governed behavior which has worked well in the past, especially when they lack sufficient information or experience about what to expect, or when the cost of making a mistake is high. As uncertainty about cause and effect increases,

there is a greater likelihood that people will follow rules of thumb, thus making their behavior predictable. Heiner used evidence from controlled scientific experiments involving human and animal behavior (Green and Swets, 1966) to argue that people have an instinctual sense of when probabilities are in their favor or not. Reliability-driven behavior encompasses more than risk aversion. People "exhibit systematic patterns of behavior that persist even when individuals cannot discern probability information" (Heiner, 1985, p. 60). When there seems to be a greater likelihood of being wrong than of being right, people are inclined to stick with what they know, with outcomes where they stay in control.

Heiner formally defined a reliability condition (1983, 1985), a formula which spells out the trade-off that "an agent must select an action less frequently if required to be more reliable in order to benefit from selecting it" (1985, p. 74). This theoretical construct was further developed into a joint reliability condition (Heiner, 1988), where the reliability of behavior is modeled as a binding constraint in decision making. Reliability theory offers two suggestions germane to economic analysis of how farmers make choices about adopting risky technologies. First, it may be appropriate to model uncertainty about technology parameters as a constraint to adoption. Second, taking account of imperfect information and inexperience with a new technology as sources of uncertainty may improve the descriptive and predictive power in *ex ante* forecasting of economic behavior.

Psychophysics and Psychometrics

The scientific basis for Heiner's reliability theory is signal detection theory, (Green, 1992; Green and Swets, 1966), a research paradigm in experimental psychology. Sensory perception is the subject matter used for theory-building (psychophysics), as well as for rigorous controlled experiments (psychometrics) to test theoretically-based hypotheses.

In a psychometric experiment, an observer is asked to report whether or not she hears a signal. Several aspects of the observer's listening conditions are controlled: the frequency with which the signal is sent, the pitch and intensity of the signal, and the level of background noise distorting its detectability. The observer reports either that the signal is present or that no signal is present. She is always either right or wrong. There are two ways to be right. One way to answer correctly is to say there was a signal when, in fact, it was present--a "hit"--corresponding with the conditional probability $P(S|s)$. Another correct response is to report hearing nothing when, in fact, there was only background noise, $P(N|n)$. There are two types of wrong answers, Type I and Type II errors. One mistaken response is to report that the signal was present when there was no signal, $P(S|n)$--a "false alarm"--which is a Type I error. The other wrong answer, a Type II error or $P(N|s)$, is reporting no signal when, in fact, the signal was present. The cumulative probabilities, $P(s)$ and $P(n)$, are calculated from count data from a series of trials where either a signal is sent or not, and it is recorded whether or not the observer reports hearing a signal.

Over numerous repetitions of an experiment where signal and noise levels are varied under controlled conditions, performance is recorded. From these experimental data, a likelihood ratio (hits over false alarms) is computed to describe the performance over a series of trials as a joint function of reliability and competence. The key insight from signal detection theory germane to the analysis of economic behavior is that two distinct sets of factors contribute to the complexity which conditions real-world decision making.[2] One factor is the interaction between the strength of the signal itself and the level of dissonance from the noise masking the signal. These factors are exogenous. The other factor is endogenous: the skill of the decision maker in distinguishing signals from noise. Judgment and experience make a difference in the quality of the information being assimilated, and in the decision maker's ability to sort out what is important from a chaotic mix of signals and noise. In psychometric analysis, these are measured as separate and then modeled as joint determinants of performance. By analogy, competence and reliability are appropriately viewed as distinct but related facets of complexity which condition economic behavior.

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[2]There is a methodological difficulty with applying concepts from signal detection theory directly to economic analysis. The data analyzed to calculate a hit/false alarm ratio are observed from multiple repetitions of a controlled scientific experiment. When producers make decisions about adopting a new technology, however, their economic behavior never involves multiple repetitions under controlled conditions. To model economic behavior, concepts from signal detection theory could be tested using data from experimental economics. Techniques from psychometrics do not, however, translate directly to empirical analysis of farmers' decision making about whether and when to adopt a new technology.

In summary, there are three ways to enhance signal detection performance: to strengthen the signal, to reduce the noise, or to improve the detector's skill. These three strategies have implications for policy design and implementation geared toward promoting technology adoption. They constitute sound criteria either for evaluating or for finetuning policy instruments. For example, if few farmers are adopting what seems to be a promising new technology, the diagnosis may be either inadequate information about its beneficial attributes (weak signal) or misinformation about costs and returns (too much noise). When a technology is risky, investment in human capital--offering farmers opportunities to hone their management skills and to enhance their competence in processing complex information--may be the best policy.

Bounded Rationality, Satisficing and Sequential Decision Making

Although Simon pre-dated Heiner, the conceptual starting place for Simon's modeling of economic behavior (1955, 1956, 1978, 1979), is where Heiner's reliability theory left off: with the tradeoff between competence and difficulty in performing complex tasks (hits and false alarms in signal detection theory). Simon said that bounded rationality is the cause of this tradeoff. Under complexity, cognitive constraints boggle the best intentions to optimize. Ideally, decision making in a dynamic setting requires weighing numerous tradeoffs simultaneously; in the real world, important information is often missing or misleading. Key outcomes are often jointly determined. The starting premise for a theory of bounded rationality is that, pragmatically, it is impossible and inefficient to optimize everything all at once.

A theory of bounded rationality accounts explicitly for constraints on human cognitive capacity. The implication of bounded rationality is that "in a world where attention is a major scarce resource, information may be an expensive luxury, for it may turn our attention from what is important to what is unimportant. We cannot afford to attend to information just because it is there" (Simon, 1978, p. 13). Simon coined the term "satisficing" to summarize the behavioral mechanism for allocating precious attention properly when faced with complexity. People focus on what seems most important. They reframe big problems into smaller problems, and assimilate only the information required to solve them. They replace abstract, global goals with subgoals which have observable, measurable outcomes. Huge objectives are divided into manageable tasks. Satisficing is converting optimal goals into satisfactory goals.

Past experience is a powerful force in determining satisficing behavior. Heuristics govern normal search procedures: "when a task environment has a patterned structure, so that solutions to a search problem are not scattered randomly throughout it, but are located in ways related to the structure, then an intelligent system capable of detecting the pattern can exploit it in order to search for solutions in a highly selective way" (Simon, 1978, p. 12). When grappling with a complex task, it is instinct to seek familiar ground. There is considerable inertia against changing a rule of thumb which works.

Satisficing involves learning to solve new problems by remembering and replicating successful solutions to similar problems in the past. Because of bounded rationality, it pays to search the familiar first, because decision errors accumulate

relatively rapidly in unfamiliar territory. Straying from the familiar means that things get progressively more complicated. In response to profound changes--triggered, for example, by an exogenous shock--it makes sense to divide multi-faceted problems into smaller tasks according to tried-and-true heuristics rather than trying to tackle everything all at once. Sequencing is an important satisficing mechanism. Information-gathering is a sequential process.

The concept of sequencing is useful in describing how a farmer reacts to the opportunity to adopt a new technology. At first the complexity of the decision whether to adopt is overwhelming. Information is sketchy, uncertainty abounds. It is reflex to respond initially by defaulting to the simplest possible decision rules which means adhering to the status quo. Due to satisficing instincts, most farmers initially conduct business as usual, neglecting to consider the technology. Over time, as neighboring farmers begin to adopt the technology, it becomes more difficult to ignore. Information from watching the neighbor's technology perform is a basis for judging its cost-effectiveness. Over time, signals about whether to adopt become clearer. Gradually these signals become more and more difficult to ignore. Well-ingrained choices based on heuristics are no longer optimal. This phenomenon is a joint function of an accumulation of evidence about the probability of success from adopting the technology and the farmer's willingness to consider such information.

To begin assimilating information about a technology adoption opportunity often requires overcoming inertia. "The state of information may as well be regarded as a characteristic of the decision maker as a characteristic of his environment"

(Simon, 1955, p. 100). The threshold at which a farmer deems it worthwhile to learn about a new technology is a joint function of the difficulty of the decision (exogenous factors, in particular, the strength of the signal and the level of noise) and of the decision maker's competence in deciding, which is endogenously determined. Heiner (1983) labeled the interplay between competence and difficulty as "the C-D gap." A key insight from behavioral economics relevant to modeling farmers' responsiveness to a new technology is this conceptual framework for identifying the factors which make a difference in pinpointing this trigger. The trigger is a uniquely-determined point at which the farmer has assimilated evidence in favor of adopting which outweighs any evidence to the contrary, as conditioned by the C-D gap.

Economic Research on Technology Adoption

The second half of this chapter is an overview of the standard approach to modeling technology adoption and diffusion. First is a description of prototypical analysis of adoption. Then, three issues germane to empirical research on adoption are discussed: the dynamic nature of technology choice; the problem of measuring adoption; and the notion of *ex ante* forecasting of whether and when producers are likely to adopt.

Prototypical Analysis of Technology Adoption

An historical, cross-sectional analysis comparing the rate of adoption of hybrid corn seed across the United States was the seminal--no pun intended--study of the

diffusion of a revolutionizing technology (Grilliches, 1957). In the early 1930s, farmers trying high-yielding varieties were few and far between. Thirty years brought major change: hybrid corn had been adopted by virtually all farmers across the United States by 1960 (Dixon, 1980). The technology spread first and fastest in the Corn Belt where almost all Iowa farmers were using hybrid corn by the mid-1940s. In contrast, it was not until the mid-1940s that farmers in the South started to experiment with or even to learn about hybrid corn. The objective of Grilliches' statistical analysis of time-series data (1932 - 1956) was to test which economic factors best explained differences in the rate of acceptance of hybrid corn across states.

A substantial proportional of the cross-sectional variation in the rate of acceptance of hybrid corn in the United States was well explained statistically by "differences in measures of average profitability, differences in average corn acres, and pre-hybrid yields" (Grilliches, 1957, p. 520). In other words, adoption varied as a function of how much improvement a farmer experienced immediately upon planting and harvesting an improved crop variety. The benefits from adopting high-yielding corn seed often outweighed the costs in the same season it was first adopted. News of success travels fast. For the Corn Belt, where hybrid varieties were highly cost-effective, the diffusion curve was steep (an S-shaped graph of the cumulative distribution of the proportion of the crop acreage under improved varieties over time). By comparison, where the marginal yield increase from planting hybrids was less significant, the diffusion of the new technology was more gradual.

The degree of certainty concerning the performance of a new technology makes a difference in its adoption. Where the cost-effectiveness of a new technology is evident and immediate, its adoption is rapid and easily predicted by economic factors. Prototypical economic analysis of technology adoption has enjoyed its greatest successes in predicting farmers' responsiveness to innovations such as water-saving irrigation devices (Caswell and Zilberman, 1985, 1986; Lichtenberg, 1989; Dinar and Yaron, 1990), where there is a convincing argument that the financial benefits of adopting outweigh the costs. The more obvious and the less risky the benefits, the more straightforward the farmer's decision making about adoption and, therefore, the greater the predictive power of economic models of technology adoption and diffusion.

Soil conservation practices and integrated pest management (IPM) strategies are examples of technological innovations whose payoffs are risky. Benefits from adoption are likely to manifest themselves gradually but also to be long-lasting; choices about whether to adopt these technologies, therefore, require a multi-period decision frame. Along with their positive on-farm effects, the benefits from soil conservation may extend downstream, just as on-farm IPM benefits may also spill over to benefit neighbors. Accordingly, the decision-making process about adoption of these technologies may involve factors in addition to cost-effectiveness, such as altruism. These complexities can undermine the predictive power of the standard technology adoption model. On one hand, from empirical studies concerning farmers' responsiveness to technologies like soil conservation and IPM, it is difficult to

generalize about adoption behavior: "for a variety of reasons, some methodological in nature, the research that has been done tells us precious little about which farmers conserve and why" (Lockerwetz, 1990). On the other hand, where the standard adoption model has not fit perfectly is where empirical researchers have made the most important strides: in tailoring behavioral hypotheses to take account of risk considerations and, more broadly, in modeling adoption with a process orientation.

Technology Adoption as a Dynamic Problem

A dynamic process is implicit in decision making about technology adoption. Schultz (1975) suggested equilibrium concepts as a basis for modeling technology adoption: over time, farmers learn what they can do with what they have. They become adept at allocating their resources efficiently. Over time, their farming practices become routine; that is, their behavioral patterns tend toward a steady state. An opportunity to adopt a new technology is a shock to well-entrenched habits of resource allocation which throws farm management planning into disequilibrium. The decision process about how to accommodate the technology requires weighing trade-offs and then settling upon a re-allocation of resources. Once the new, expanded opportunity set is reconciled--with the new technology either being accepted, rejected, or partially adopted--there is a new equilibrium. Adoption is not an instantaneous phenomenon. "Regaining equilibrium takes time, and how people proceed over time depends on their efficiency in responding to any given disequilibrium and on the costs and returns of the sequence of adjustments available to them" (Schultz, 1975, p. 829).

Choice about technological innovations is best modeled as a process--the process of equilibrating--beginning with the perception of a broader opportunity set and followed by assimilation of information about the newly available technology. Recognition and learning take time. This process orientation was implicit in studies of aggregated adoption behavior using time-series data, accomplished through comparisons of differences in diffusion rates across states or regions (Grilliches, 1957; Lichtenberg, 1989). The majority of recent empirical research, however, has focused on individual adoption behavior which involves statistical analysis of cross-sectional data. Cross-sectional data constitute a snapshot of a single stage in the adoption process.

Using cross-sectional data to model the steps in a dynamic process of recognizing an opportunity and learning about a new technology, Ervin and Ervin (1982) specified three stages in the decision making process about adopting soil conservation practices: perception of an erosion problem, decision to use soil conservation practices, and soil conservation effort. They measured explanatory variables to characterize these three increments in the adoption process. Statistical analysis tested the extent to which the sharpness of farmers' perceptions of an erosion problem and the extent of farmers' knowledge about conservation--their progress in the learning process--was correlated with adoption behavior. Similar approaches were developed by Norris and Batie (1987) and by Gould, et al. (1989).

Ervin and Ervin expressed concerns about the inherent limitations of modeling an adoption process with cross-sectional data.

> As evidenced by the many insignificant variables, however, the majority of variation in any of the dependent variables was not explained. Analysis of residuals did not reveal important misspecified or omitted variables, and serious multicollinearity was not present. **Perhaps attempts to explain the dynamic process of conservation practice use with static reduced form models will always fall short.** [emphasis added] . . . A major liability of undertaking cross-sectional analyses in this research area seems to be the risk of low total explanatory power. (Ervin and Ervin, 1982, p. 290)

They suggested a longitudinal study as an alternative approach, a mechanism for more appropriately modeling the dynamics of adoption. Panel data--taking a series of snapshots of adoption behavior over time--was proposed as an ideal medium for modeling individual decision making about technology adoption. Unfortunately, however, panel data sets tracking adoption are expensive to collect and thus rare.

Byerlee and Polanco (1986) implemented empirical research using a panel data set to analyze the stepwise approach Mexican farmers followed in deciding whether to adopt high-yielding varieties, fertilizers, and pesticides. These three technologies were offered as a package because a hybrid seed yields best when fertilized and protected from pests. Adopting the complete package is the most cost-effective, given sufficient rainfall. Contrary to what those disseminating the technology package expected, however, early adopters often experimented with only the seed without the fertilizer. Analysis of panel data from interviews with 54 farmers between 1975 and 1980 indicated that Mexican farmers' decisions to adopt the technology package in increments was a near-optimal response to risk, mainly due to variability in

agroclimatic conditions (particularly drought). Statistical analysis identified learning[3] as a factor in explaining changes over time in farmers' responsiveness to high yielding varieties. The analysis explicitly accounted for risk constraints and the nature of the dependent variable in the statistical model allowed for farmers' choices either to adopt the whole package or to experiment with intermediate options.

Measuring Adoption

The flexibility to depict partial adoption enhances the predictive power of empirical models of adoption behavior. In cross-sectional analysis, a diverse set of measures have been used as proxies for adoption behavior; in conservation adoption research, for example, dependent variables have included the number of conservation practices used on the farm (Ervin and Ervin, 1982) as well as the dollar amount spent on conservation in a given year (Norris and Batie, 1987). Incongruent empirical results from fitting equations with the same explanatory variables and different dependent variables indicated that "the decision to use a larger number of practices and soil conservation effort are not conceptually substitutable" (Ervin and Ervin, p. 291). Attempts to generalize about what factors are important determinants across empirical studies of adoption behavior using statistical results from cross-sectional analysis have been handicapped by differences in dependent variables, as well as by

[3]Smith and his colleagues (1988a, 1988b, 1990) collected panel data to analyze how homeowners learn about radon's risk. This empirical research offers methodological and conceptual insights germane to modeling the learning process which drives adoption behavior.

differences in the mix of explanatory variables used in statistical models (Lockerwetz, 1990; Purvis, 1989a).

Recent discussions in the literature (Norris and Batie, 1987; Ervin and Ervin, 1982) of the importance of measuring dependent variables consistently promise to promote standardization, thus facilitating future attempts at comparative analysis of empirical research results concerning adoption behavior. An equally important force toward improving the precision of the specifications of dependent variables in adoption studies is the growing use of limited-dependent variables (Maddala, 1983) in econometric analysis of cross-sectional data. Use of multi-nomial logit equations (Caswell and Zilberman, 1985; Garcia et al., 1983), Tobit equations (Norris and Batie, 1987; Purvis et al., 1989a, 1989b), and two-stage specifications with limited-dependent variables (Gould et al., 1989; Rahm and Huffman, 1984; Rook and Carlson, 1985; Burrows, 1983) has provided a framework for modeling with a process orientation and has sharpened the measurements of adoption behavior employed in empirical studies. These notions--of modeling with a process orientation and of employing a precise definition of adoption behavior--played a role in the design of the empirical research presented in this thesis, even though the analysis itself was based on simulation methods rather than econometric analysis.

Ex Ante Forecasting of Adoption

Given that adoption involves a learning process, one objective of policy design and implementation is to structure incentives or interventions in order to facilitate

information delivery about a new technology, toward promoting its adoption. For policy purposes, a built-in limitation of using cross-sectional data or time-series data for empirical analysis of adoption behavior is that such data only exist when the adoption process is well underway. Lessons learned *ex post* offer guidance about what to replicate and what to avoid in policies pertaining to the next new technology introduced, or when introducing that same technology in a different place. The extent to which *ex post* analysis has utility for designing and implementing future policies, however, depends upon the similarities between the circumstances surrounding a past technology adoption opportunity and a new situation. Empirical evidence suggests that similar policy instruments for promoting technology adoption can have quite different results under different circumstances.

Kalaitzandonakes and Boggess (forthcoming) proposed a conceptual framework designed to predict adoption behavior based on *ex ante* knowledge about the technical specifications and the expected performance of the technology, as well as the pre-adoption allocation of resources on the farm. Their theoretical model represented the adoption process as a two-stage problem. First, the fixed factors of production are allocated to a new technology based on farmer risk preferences, and then profit is maximized, conditional on this resource allocation. Given estimates of current on-farm resource endowments, of farmers' risk preferences, and of the expected production efficiency improvements from adopting the new technology, it is possible to predict, *ex ante*, the optimal rate of adoption and to plot an expected diffusion curve. For policy purposes, this *ex ante* baseline assessment offers a basis for

predicting whether existing incentives and interventions are adequate to achieve policy objectives. If the projected adoption process does not match with policy goals, then incentives and interventions can be modified accordingly, in order to improve the correspondence between policy objectives and results in actual policy implementation.

This notion of *ex ante* forecasting of adoption behavior has been introduced in the theoretical literature on adoption (Kalaitzandonakes and Boggess, forthcoming; Antle, 1989), but has not been implemented empirically, nor has it been applied specifically to agricultural and environmental policy analysis. The research reported in this thesis is an attempt to further develop these concepts through empirical analysis.

A conceptual framework from financial economics for analyzing investment under irreversibility and uncertainty lends itself to *ex ante* forecasting of adoption behavior. This theory and methodology are an outgrowth of option pricing models, used to assess, *ex ante*, stockholders' willingness to pay for options contracts. Option pricing is jointly determined by the estimated price of the underlying asset and by the level of uncertainty about that valuation. Similarly, what determines the value of investing is the anticipated cost-effectiveness of the investment and the estimated variance associated with that prediction, either based on past performance or on information from others' experiences investing. The next chapter describes the theory of investment under irreversibility and uncertainty, a conceptual framework applicable to *ex ante* forecasting of whether or when farmers are likely to adopt a technology.

CHAPTER 3
THEORY

The objective of this chapter is to describe the theory of investment under irreversibility and uncertainty. "As an emerging literature has shown, the ability to delay an irreversible investment expenditure can profoundly affect the decision to invest" (Pindyck, 1991b, p. 1110). This theory provides the basis for *ex ante* empirical analysis of dairy producers' decisions about adopting free stall technology.

Uncertainty and irreversibility associated with dairy investments may help to explain why free stall technology has been slow to catch on in the South. To build a free stall barn and accompanying waste management system requires an investment of approximately $950 per cow (Pagano, et al., 1993b), which is a sunk cost--an expenditure which cannot be completely recouped if the producer later decides to get out of free stall dairying. It takes at least five years to pay back a loan for a free stall investment. In addition, uncertainty about milk prices, about the costs of environmental compliance, and about the operational efficiency of free stall dairy facilities complicates the investment analysis.

The opportunity to invest does not disappear if a dairy producer decides to wait. On the contrary, empirical analysis of dairy investment behavior in Okeechobee, Florida, in response to the 1987 Dairy Rule, showed that deferred

adoption strategies were more profitable than early adoption (Boggess et al.,1991). Postponing action allows him or her to collect more information about the evolution of environmental compliance requirements and about the experiences of others who adopt free stalls. The decision to adopt free stall dairy technology is not only whether to invest, but also when.

The basis of the theory of investment under irreversibility and uncertainty is an analogy: between the Black-Scholes option pricing model (1973) in financial economics--also known as contingent claims analysis--and the notion that an opportunity to invest is really a series of choices whether to invest--that is, options. The first section of this chapter describes option pricing, a methodology for calculating the value of an option and for pinpointing the optimal time to exercise an option. The second section is a discussion of the theory of investment under irreversibility and uncertainty. This theory builds on standard investment theory, where the criterion for an acceptable investment is a positive net present value. The final section outlines a conceptual framework for empirical measurement of the effect of uncertainty and irreversibility on the decision whether and when to invest in free stall facilities and then spells out a set of testable hypotheses and procedures for hypothesis testing.

An Overview of Option Pricing Theory

A stock option is a contract specifying the right but not the obligation to buy or sell stock within a given time period at an agreed-upon price, called the strike

price or the exercise price. An American option can be exercised any time up to its expiration date; a European option can be exercised only on the expiration date. Stock options and forward contracts on commodities are familiar examples of contingent claims or derivative assets (Mason and Merton, 1985; Rubinstein, 1987). The basic notion is that the value of a contingent claim (or a derivative asset) is contingent upon (derives from) future outcomes. The value of a stock option depends on whether the market price of the stock is above or below the strike price specified in the option contract. Trading stock options became big business twenty years ago, when an organized market for the exchange of standardized option contracts opened.[1]

It is coincidence that Black and Scholes (1973) published their seminal article on the theory of option valuation the same year an organized options market was formed. This coincidence of timing provided opportunities to test the model, and to broaden its applicability to a wide range of real-world market transactions. This timing contributed to its reputation "as the most successful theory not only in finance but in all economics" (Ross, 1991). Pricing options on stocks was the focus of the Black-Scholes model and of most of the subsequent theoretical research on options in financial economics. This conceptual framework applies equally well to a wide range of economic decisions which involve implicit options on other underlying assets.[2]

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[1]The Chicago Board of Options Exchange opened on April 26, 1973. Volume on the Chicago Board of Options Exchange surpassed the American Stock Exchange in late 1974 (Copeland and Weston).

[2]Stock options are most common. In this discussion, the more general term "underlying asset" is used, to reinforce the notion that options (real or hypothetical) can be written on a broad class of tradable assets.

Contingent claims analysis is an inclusive and descriptive label for these ideas and techniques.

This section begins with a heuristic discussion of how to value a call option. The second topic is the theoretical underpinnings of contingent claims analysis, described using the binomial version of the option pricing model. Finally, the Black-Scholes option pricing formula is stated concisely and interpreted.

Valuing a Call Option

A call option is the right to buy an underlying asset for a given price at a specified time. Five factors determine the value of a call option: its strike price (X), the price of the underlying asset (S), the instantaneous variance (σ^2) on the price of the underlying asset, the time (T) remaining before the option expires, and the risk-free interest rate (r). The only opportunity to exercise a European call option is on its expiration date; thus, its terminal value is important. Likewise, the best time to exercise an American option on an underlying asset which pays no dividends[3] is on the maturity date.

Valuing a call option on the date it expires is straightforward. Figure 3-1 plots the call price (C) of an option at maturity as an increasing function of the price

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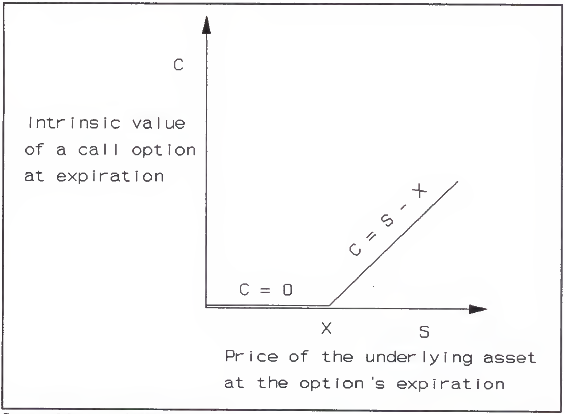
[3]In the discussion of option pricing, for simplicity we assume the underlying asset earns no dividends during the term of the contract. This assumption will be relaxed in the next section of this chapter, in the discussion of investment under irreversibility and uncertainty, a framework for analyzing investments which yield a constant stream of returns, such that there is an opportunity cost to waiting to invest.

For a proof of the equivalence of an American call option and a European call option, please refer to Varian (1987, p. 62 - 64).

of the underlying asset (*S*). At the end of an option contract, if the strike price (*X*) is less than the price of the underlying asset, then the higher the price of the underlying asset, the more valuable the option. Its exact value is the call price, calculated as the current price of the underlying asset less the strike price ($C = S - X$). If the price of the underlying asset is below the strike price, then the call option is worthless ($C = 0$).

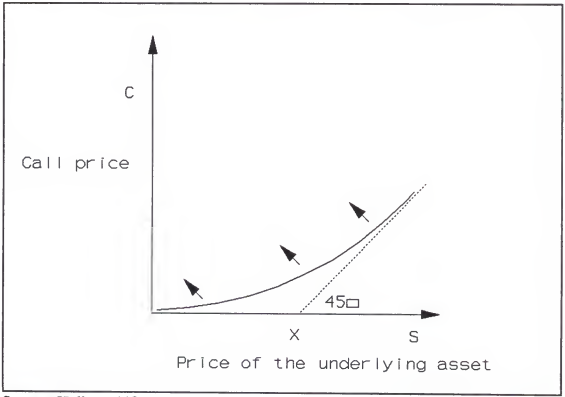
Figure 3-1: Option Value Upon Expiration



Source: Mason and Merton, p. 12.

The call price of an option is its traded value, the price at which someone would be willing to buy or sell it. The call price equals the intrinsic value of the option when the contract expires. Its intrinsic value is the payoff an option would yield if it were exercised immediately. On the graph in Figure 3-2, the intrinsic value is represented as being equal to the horizontal axis up to *X*--and then it is represented by the dotted 45° line where $S > X$. Any time before it expires, the call price of an option is higher than its intrinsic value. Raising the call price shifts the call price function upward, in the direction of the arrows drawn in Figure 3-2. The higher the current price of the underlying asset, the higher the call price.

Figure 3-2: Call price of an option



Source: Hull, p. 112.

Four additional factors increase the call price of an option relative to its intrinsic value, *ceteris paribus*. First, the lower the strike price, the higher the call price of an option. A lower strike price increases the likelihood that the option will expire "in the money." Second, the higher the risk-free interest rate, the greater the difference between the call price and the intrinsic value of an option. Third, increasing the instantaneous variance of the underlying asset on which the option is written raises its call price. Volatility of expected returns on an underlying asset makes it valuable to hold an option rather than holding the asset itself.

The final factor is time: the more time until an option expires, the greater its call price. A more distant maturity date allows more possibilities for upside variation in the stock price, assuming a constant instantaneous variance. The longer the option contract, the greater the probability that the option will expire "in the money." Protection from downside risk also accounts for willingness to pay more for an option contract the longer before it expires. To exercise an option early is to forego the insurance benefits from waiting until the expiration date. "Once the option has been exercised and the exercise price has been exchanged for the stock price, this insurance vanishes" (Hull, 1989, p. 112). Dixit (1992b) labeled this implicit protection against unanticipated price fluctuations a "holding premium."

An option on an asset which pays no dividends should never be exercised early. Hull (1989, p. 112) explained the intuition behind this notion:

> If an investor has a call option on a stock and feels that the price is likely to go down, he or she should not exercise early. Instead, the option should be sold. The option will be bought by another investor who does not share the first investor's beliefs about the prospects for

> the stock. Such an investor must always exist; if all investors felt the same as the first investor, the stock price would be lower.

Similarly, the expectation that the price of the underlying asset will go up is not sufficient reason to exercise an option before it expires. Expectations concerning the price of the underlying asset, per se, have no effect on the intrinsic value of an option. Only the current, observed price of the underlying asset is required to estimate the call price and thereby to estimate option value. The effect of expectations about the price of the underlying asset enter the option pricing formula through its variance: higher variance means higher option prices, *ceteris paribus*.

Theoretical Underpinnings of Option Valuation

The crucial insight driving the Black-Scholes option pricing model (1973) is the possibility of using a synthetic portfolio, comprised of a long position in the underlying asset and a short position in call options, to estimate the value of an option. The objective of the portfolio is to specify a combination of investments (some mix of options and the underlying asset) such that, over a short time interval, the payoff from holding either the underlying asset or the options are exactly the same--assuming no arbitrage opportunities.[4] "In an intertemporal setting as well as in a static setting, two things which can be shown to be equivalent must sell for the same price" (Cox and Ross, 1976, p. 146). The portfolio is updated to show how option value changes over time, with a "dynamic replicating strategy" (Rubinstein,

[4]Arbitrage is "arranging a transaction involving no cash outlay that results in a sure profit" (Varian, 1987, p. 55).

1987). Payoffs from the underlying asset are modeled as if they fluctuate stochastically following a continuous path with constant variance. The modeling involves incremental adjustments of the proportions of the portfolio holdings in order to keep payoffs from the long and short positions exactly equal.

A version of the Black-Scholes formula using a binomial variate to represent random movement in the price of the underlying asset highlights the fundamental economic principles of option valuation by arbitrage methods (Cox, Ross and Rubinstein, 1979). Over an infinitesimally small time interval, assume that the price of the underlying asset moves either up or down by some fixed percentage; specifically, the price S either increases by a factor of u, or moves down by a multiplicative increment of d.[5] The composition of the portfolio is such that $u > r > d$, where r is the risk-free interest rate. This inequality rules out profitable risk-free arbitrage opportunities. The value of a call option if the price of the underlying asset goes up is defined as C_u; if the price of the underlying asset goes down, then the call price for the option contract is C_d.

There are four steps in calculating the value of an option. The first step is to construct a risk-free hedged portfolio. The portfolio is comprised of one share in the underlying asset and m call options written against it. If the market goes up, then the

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[5]An estimate of the instantaneous variance (σ) on the price of the underlying asset is all that is needed to determine the coefficients u and d. The value uS is one standard deviation above the price of the underlying asset at the beginning of the period, and dS is one standard deviation below. If S is normally distributed, then $u = -d$.

The hedging probability (q) is the likelihood of S increasing; the probability of S falling is $1 - q$. If S is normally distributed then $q = 0.5 = 1 - q$.

call price is $C_u = uS - X$. If the market falls, then the option is worth nothing ($C_d = 0$) because the strike price is greater than the price of the underlying asset. Setting equal payoffs from long and short positions:

$$uS - mC_u = dS - mC_d. \tag{3-1}$$

For this equality to hold requires writing m call options:

$$m = \frac{S(u - d)}{C_u - C_d}. \tag{3-2}$$

Equation (3-2) gives the hedging ratio.

The second step is to calculate what the portfolio is worth, its call price (C). This requires setting up an equation for a risk-free hedged portfolio. The expected yield from holding the portfolio for one period is the risk-free interest rate (r). To form a risk-free hedged position, on the left hand side, the current value of the portfolio is multiplied by the risk-free rate. The right hand side is the expected value of the portfolio when the option contract expires, given that the price of the underlying asset goes up. Setting these equal,

$$r(S - mC) = uS - mC_u; \tag{3-3}$$

thus, rearranging gives:

$$C = \frac{S(r - u) + mC_u}{mr}. \tag{3-4}$$

The next step is to substitute the hedging ratio, Equation (3-2), into Equation (3-4),

$$C = \frac{\left[\frac{r-d}{u-d}C_u + \frac{u-r}{u-d}C_d\right]}{r}.$$

Equation (3-5) is the call price of an option contract.

The final step is to simplify, defining $p \equiv (r - d)/(u - d)$ and $1 - p \equiv (u - r)/(u - d)$. Then,

$$C = \frac{[pC_u + (1 - p)C_d]}{r}. \quad (3\text{-}6)$$

This is the exact value of a call option, one period prior to its expiration. Its interpretation is straightforward: by definition, the value of C_d is zero because $S < X$. The call price is the intrinsic value of the option if the price of the underlying asset exceeds the strike price, C_u, multiplied by the probability of that occurring, p, discounted at the risk-free interest rate.

An important implication from Equation (3-6) is that risk preferences play no role in determining how much an option is worth. Risk-neutral option traders expect a risk-free yield from investing. By definition,

$$q(uS) + (1 - q)(dS) = rS\ . \quad (3\text{-}7)$$

Note that p is a risk-neutral hedging probability, since

$$q = \frac{(r - d)}{(u - d)} = p\ . \quad (3\text{-}8)$$

"Hence, the value of the call option can be interpreted as the expectation of its

discounted future value in a risk-neutral world" (Cox, Ross and Rubinstein, 1979, p. 235-236). It is not necessary to know the investor's expectations about what will happen to the price of the underlying asset in order to estimate option value. Rather than specifying, *ex ante*, the hedging probability (q), probability weights (p and $1 - p$) are determined endogenously. This reduces the data requirements for estimating option value: only an estimate of how much the price of the underlying asset is likely to move up or down (an estimate of the instantaneous variance of S) is required.

For a single increment of the option contract, the hedging probability (p) gives the likelihood of the price of the underlying asset rising in that period, and Equation (3-6) estimates the option value for that particular interval. The binomial model generalizes to n time periods: the time remaining until the option expires is divided into n discrete increments, S is the current market price of the underlying asset, and X is the strike price. The stock must move up at least a times over the next n periods for the option to finish in-the-money. The binomial call price formula, at $t = j$, is

$$C = \frac{\left[\sum_{j=a}^{n}\left(\frac{n!}{j!(n-j)!}\right)p^{j}(1-p)^{n-j}[u^{j}d^{n-j}S - X]\right]}{r}. \tag{3-9}$$

Separating the binomial option pricing formula into two components,

$$C = S\left[\sum_{j=a}^{n}\left(\frac{n!}{j!(n-j)!}\right)p^{j}(1-p)^{n-j}\left(\frac{u^{j}d^{n-j}}{r^{n}}\right)\right] - Xr^{-n}\left[\sum_{j=a}^{n}\left(\frac{n!}{j!(n-j)!}\right)p^{j}(1-p)^{n-j}\right] \tag{3-10}$$

Equation (3-10) is a multi-period binomial version of the single-period formula for a

call price, Equation (3-6), restated as $C = (pC_u)/r = (S - X)/r$, weighted by the probability of the option finishing in the money. In the limit, the sum of independent binomial normal variates approximates a random walk (Dixit, 1992a).

The Black-Scholes Option-Pricing Model

In the original continuous-time formulation of the option pricing model, Black and Scholes (1973) depicted the stochastic variable, the price of the underlying asset (S), as a random walk. They modeled S as a geometric Brownian motion process:

$$\frac{dS}{S} = \mu dt + \sigma dz \tag{3-11}$$

where dz is an increment of a Wiener-Gauss process, $dz = \varepsilon(t)(dt)^{1/2}$ and $\varepsilon(t)$ is the cumulation of independent identically normally distributed increments (Dixit, 1992a). Over any finite interval of time, percentage changes in S, dS/S, are normally distributed, and absolute changes in S are log-normally distributed (Dixit, 1991b). There is a negative or positive trend (μ) in random price movements. The instantaneous variance (σ) of the price of the underlying asset sets the steps in the random walk, or, equivalently, describes the time path of the random process.[6]

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[6]By definition, this is an Ito process: the trend and volatility of the time path are determined from observed statistics on the current state of the random variable, and are also a function of time (Dixit, 1992a, p. 9).

The feature which makes the calculus of Brownian motion different from the calculus of non-random variables is that the variance of the increments of S is a linear function of time (Dixit, 1992a, p. 5). Cumulative variance, therefore, is an increasing function of time.

Using Ito calculus, a differential equation with boundary conditions is required to set up a risk-free portfolio and a replicating strategy to account for stochastic movements in the price of an underlying asset. The logic behind this differential equation[7] directly parallels the process described above with the binomial model, in Equations (3-1) through (3-11). Cox, Ross and Rubinstein (1979, p. 246-254) showed that, in the limit, a multiplicative binomial variate (used to model the distribution of the expected price of the underlying asset) approximately equals the log-normal distribution. Using this result, they developed a clear treatment of how the binomial version of the model--that is, Equation (3-11)--converges to the Black-Scholes (1973) option pricing formula as the time interval of the option contract is divided into more and more discrete sub-intervals. The limiting case of the binomial model is the Black-Scholes (1973) option pricing formula:

$$C = S\,N(d_1) - Xe^{rt}\,N(d_2)\,. \tag{3-12}$$

N(•) denotes a normalized variate, where

$$d_1 = \frac{\ln(S/X) + rt}{\sigma\sqrt{t}} + \frac{1}{2}\,\sigma\sqrt{t} \tag{3-13}$$

$$d_2 = d_1 - \sigma\sqrt{t}. \tag{3-14}$$

The interpretation of Equation (3-12)--the Black-Scholes (1973) option pricing formula--is that the traded value of the call is the price of the underlying asset, minus

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[7]The differential equation and its solution was given in Black and Scholes (1973); it is summarized concisely in Mason and Merton (1985, p. 19 - 22); the mathematics are explained in Dixit (1992a, 1992b) or in Pindyck (1991b).

the discounted value of the strike price with each component weighted by a probability (Copeland and Weston, 1988). The fundamental elements of this equation representing option value--where $C = (S - X)/r$, weighted by the probability of the option finishing in the money--correspond with the binomial version of the model in Equation (3-10) above. The probability $N(d_1)$ is the inverse of the hedge ratio, which means that a risk-free hedged portfolio includes $1/N(d_1)$ call options written against the stock. The probability $N(d_2)$ is the likelihood that, on the expiration date, the price of the underlying asset will be higher than the strike price.

This calculation gives an estimate of option value. Only five data points are required: the strike price, the risk-free interest rate, the duration of the option contract, the current market price of the underlying asset, and the instantaneous variance on the price of the underlying asset. To estimate willingness to pay for option contracts prior to Black and Scholes (1973), market-equilibrium models were employed which required restrictive assumptions to describe option traders' risk preferences. The data requirements were cumbersome, and the complexity of the models was daunting. The clever idea of using arbitrage principles to create a synthetic portfolio as the basis for pricing options constituted a significant theoretical contribution and spawned important empirical applications.

Understanding the mechanics of option pricing provides the tools required to apply contingent claims analysis to other problems sets. Black and Scholes (1973), in their concluding remarks, suggested another application: "it is not generally realized that corporate liabilities other than warrants may be viewed as options, ... that the

stockholders have the equivalent of an option on their company's assets" (p. 649). Mason and Merton expressed the opinion that this qualitative insight--that many problem sets can be framed as options--may be of greater practical and academic significance than their quantitative analysis. The observation that a wide variety of economic decisions involve implicit options "brings many disparate phenomena into a common framework" (Dixit, 1992b, p. 108). In 1991 The Economist selected contingent claims analysis as one of the twelve most promising theories in economics, and remarked that "the only limit to the usefulness of Black-Scholes will be the ingenuity of other economists in recognizing hidden options for what they are" ("Of Butterflies and Condors," p. 59).

Modeling Investment Behavior

The focus of the second section of this chapter is an application of contingent claims analysis to develop criteria for evaluating investment projects. Mason and Merton (1985) explained the basis for using option pricing techniques to calculate how much an option to invest is worth.

> The fundamental evaluation equations of contingent claims analysis are derived from arbitrage arguments involving portfolio strategies using traded securities. One might reasonably question, therefore, the validity of such equations for evaluating capital budgeting projects which are not traded. All capital budgeting procedures have as a common objective the estimation of the price that an asset or project would have if it were traded (p. 38-39).

Modeling an investment opportunity as a series of options to invest captures the inter-temporal context for investment decision making.

This section is introduced with a discussion of how uncertainty and irreversibility influence the choice of whether and when to invest. Second, the standard economic criterion for evaluating investment opportunities (whether the net present value of expected returns is positive) is compared with a model to devise investment decision rules based on contingent claims analysis. This modified method accounts for both the value of investing and the value of waiting. The technique for choosing an optimal investment policy is displayed graphically.

Irreversibility and Uncertainty

Under many conditions, waiting to invest has value. Pindyck (1991b) and Dixit (1992b) highlighted three concepts which help to explain when and why it pays to postpone the decision to invest. First, to initiate an investment project often requires an expenditure which is irreversible. In agriculture and in industries experiencing rapid technological change, asset fixity means there is little likelihood of recovering sunk costs. Sunk costs make hasty action risky because reversing an imperfect choice can be costly. Second, payoffs from new investment projects are uncertain, and information unfolds gradually. Under complex and evolving circumstances, new information never completely eliminates uncertainty, but sometimes watching others climb the learning curve yields valuable lessons. Finally, the choice to invest is rarely now or never. Rather, the decision is usually whether to invest now, or to delay and then later re-assess. "As long as the opportunity to invest remains available, a later decision can be a better one" (Dixit, 1992b, p. 108).

Both empirical and theoretical evidence suggest that "a great deal of inertia is optimal when dynamic decisions are being made in an uncertain environment" (Dixit, 1992b, p. 108).[8] Inertia is manifest in standard operating procedures governing business investment behavior: a "hurdle rate" is the rate of return which firms expect of their investments. In evaluation of real-world capital investment projects, hurdle rates as high as three or four times the cost of capital are commonplace (Summers, 1987). McDonald and Siegel (1986) modeled investment behavior where the expected present value of future returns from a project had non-zero variance. They concluded that "for reasonable parameters it is optimal to defer investing until the present value of the benefits from a project is double the investment cost" (p. 708).

In theory, the source of the inertia which causes high hurdle rates is an economic trade-off: on one hand, investors weigh the cost of an expensive decision error (incurred if an investor were to initiate an investment only to realize--too late to recover sunk costs--that actual payoffs are lower than forecasted). On the other hand, they consider the opportunity cost of waiting (the sacrifice of potential positive payoffs, foregone over the interval before an investment is made). Optimal timing of an investment is when the probability-weighted opportunity cost of foregone benefits exceeds downside losses from a wrong investment, also weighted by its likelihood. This occurs exactly when the value of investing equals the value of waiting to invest.

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[8]One caveat applies. "Firms do not always have an opportunity to delay investments. For example, there can be occasions in which strategic considerations make it imperative for a firm to invest quickly and thereby preempt investment by existing or potential competitors" (Pindyck, 1991, p. 1111).

The value of waiting often outweighs the value of investing when the decision environment is complex. More uncertainty increases the value of an option to invest in an irreversible project, but reduces the current propensity to invest, ceteris paribus. Bernanke (1983) characterized this tendency as the "bad news principle:" when it is possible to wait, avoiding downside risk is the dominant factor in investment behavior. "A small increase in the probability of disaster cannot be offset by any potential good news in its effect on current purchases" (p. 93). Investors achieve selective risk reduction from waiting--they avert regret by postponing or exiting if outcomes are unfavorable, but still maintain upside potential. The value of this downside protection is offset by sacrificed potential investment earnings during the waiting period. In summary, "total upside probability matters, but not the shape of the distribution of revenues to the right of the optimal trigger" (Dixit, 1992b, p. 118).

Optimal Investment Policy

The rule of thumb from standard economic theory is to invest if the present value of a project is positive. Implementing an evaluation of an investment opportunity using this criterion requires three steps. First, forecast the stream of expected net returns from the project. Second, discount the expected future returns at an appropriate rate of return.[9] Third, if the present value is positive, then recommend initiating the project. An assessment based on checking the present value

[9]Theory suggests the risk-free interest rate as the appropriate discount rate for risk-neutral investors. As mentioned above, actual hurdle rates are often higher than the risk-free rate.

of an investment works well when the flows of costs and revenues associated with an investment are relatively certain, and if sunk costs are small. Applying the present-value decision rule generates a measure of the value of investing, thus providing a benchmark for judging whether an investment is worthwhile.

In the comprehensive approach to modeling investment behavior first presented by McDonald and Siegel (1986) and further developed by Dixit (1992b) and Pindyck (1991b), using the present value criterion to quantify the value of investing is a vital step in the process of pinpointing when to launch an investment project. This decision rule, however, ignores the trade-offs resulting from irreversibility and uncertainty when the investor has the option of waiting. Measuring the value of waiting and putting it together with the value of investing to determine an optimal investment decision rule is the essence of the theoretical contribution from the conceptual framework for modeling investment under irreversibility and uncertainty.

Dixit (1992b) described optimal timing of an investment as a tangency between two curves, one describing the value of investing (i_1i_2), the other describing the value of waiting to invest (w_1w_2). Four parameters[10] determine the shape and position of these curves: (1) the expected net revenues (R) from the investment; (2) the sunk cost (K) of initiating the investment project; (3) a risk-adjusted discount rate (ρ)--the opportunity cost of capital; and (4) the variance (σ^2) of expected net returns from the investment.

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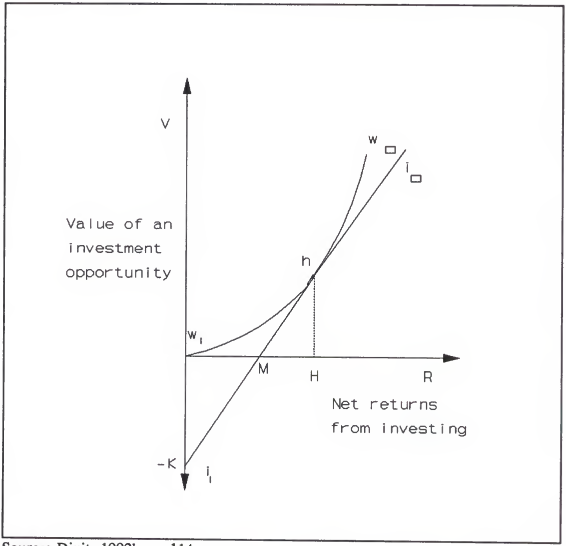
[10]These are the same as the parameters required for the option pricing formula. Expected net returns (R) substitute for the price of the underlying asset (S). The strike price (X) in this model is sunk costs (K).

The value of an investment opportunity (V)[11], graphed on the vertical axis, is an increasing function of expected net returns (R), plotted on the horizontal axis (Figure 3-3).

Figure 3-3: Optimal Investment Policy



Source: Dixit, 1992b, p. 114.

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[11]The value of an investment opportunity (V) is the value of the option to postpone investing.

The equation for the value of investing is based directly on present value calculations: the value of an investment is positive if the discounted expected returns exceed the present value of the sunk investment cost, K, or when $R/\rho \geq K$.[12] Dixit (1992b, p. 110) labeled the point of indifference between investing or not investing "the Marshallian trigger" (M). According to the present-value criterion, whenever $V(R) \geq 0$ it is worthwhile to invest--that is, at any point above M on the curve $i_1 i_2$. The hurdle rate or discount rate required to make this investment acceptable is ρ, and the Marshallian trigger is defined as $M = \rho K$. Whenever the discounted expected returns from investing are above M, the investment opportunity is rated as favorable. The origin of the curve ($w_1 w_2$), which represents the value of waiting, is where $R = 0$ and $V(R) = 0$. Avoidance of downside risk--choosing only investment outcomes where $V(R) > 0$--is reflected in the position of $w_1 w_2$. An investor who waits, with the advantage of hindsight, would exercise an option to invest only if $V(R)$ were positive. The area bordered by the curve $w_1 w_2$ and the horizontal axis to the left of H is the probability-weighted value of positive outcomes during the waiting period.

Two equations are required to describe the overall value of the opportunity to invest,

$$V(R) = \begin{cases} BR^{\beta} & \text{if } R \leq H \\ R/\rho - K & \text{if } R \geq H \end{cases} \tag{3-15}$$

the value of waiting (BR^{β}) and the value of investing (R/ρ - K). In solving these

[12]The discounted net returns, R/ρ, is the present value of an infinite stream of annuities from the investment project.

equations to derive an optimal investment decision rule, the necessary and sufficient conditions are called the value matching condition and the smooth pasting condition (Dixit, 1992a). When both are satisfied simultaneously, the two components of Equation (3-15) are tangent. The point H in Figure 5-3 represents the threshold level when the expected annualized returns from the investment project are sufficiently high to make the investment acceptable. This tangency takes into account both irreversibility and uncertainty through the value of waiting.

The value matching condition requires that $R = H$, that the solutions to the value of investing and the value of waiting be equal (their graphs must intersect). The smooth pasting condition imposes the additional requirement that the two curves be tangent, and that this tangency must satisfy boundary conditions to assure a unique optimum. The result of the smooth pasting condition is a unique point where $R = H$, derived by equating the slopes of the two equations at H. To satisfy the two conditions together requires differentiating both equations with respect to R, and setting the two equations equal to solve for H. This solution identifies the unique point where both the value matching condition and the smooth pasting condition are satisfied:

$$H = \frac{\beta}{\beta - 1} \rho K. \qquad (3\text{-}16)$$

The optimal investment trigger, H, is greater than $M = \rho K$, the Marshallian trigger, by a factor of $\beta/(\beta - 1)$. The parameter β comes from the equation for the curve $w_1 w_2$ representing the value of waiting (equivalently, the opportunity cost of

immediate action). Its formula is a function of two known parameters (ρ and σ^2).[13]

$$\beta = 1/2\left[1 + \sqrt{1 + \frac{8\rho}{\sigma^2}}\right] > 1 \tag{3-17}$$

As uncertainty about net returns (σ^2) increases, β gets larger and the difference between the Marshallian trigger and the optimal trigger increases. Raising the discount rate makes β smaller and reduces the difference between the Marshallian trigger and the optimal trigger.

Dixit (1992b) suggested defining a new hurdle rate, ρ', to show the exact effect of factoring in the value of waiting on the investment trigger. The Marshallian trigger is $M = \rho K$; this decision criterion accounts only for the value of investing. The modified hurdle rate is ρ', defined

$$\rho' = \frac{\beta}{\beta - 1}\rho. \tag{3-18}$$

Then Equation (3-16) can be rewritten as $H = \rho' K$. This revised decision rule takes into consideration both the value of investing and the value of waiting. The modified hurdle rate ρ' is useful for quantifying the difference between the Marshallian investment threshold and the revised trigger, and for structured sensitivity analysis of how changes in $\beta(\sigma,\rho)$ affect investment. The revised trigger for optimal investment,

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[13]The equation for β is derived from a Cauchy-Euler root of the differential equation used to solve for the option pricing formula. For details, see Dixit (1992a; 1992b, p. 113 and p. 129-130).

To solve for the other unknown parameter in the equation for the value of waiting--the multiplicative constant B--requires simultaneously satisfying the value-matching condition and the smooth-pasting condition.

H, provides a comprehensive criterion for evaluating investment projects under irreversibility and uncertainty.

A Conceptual Framework for Empirical Analysis

Dixit (1992b) asked whether the difference between the Marshallian discount rate, ρ, and the modified hurdle rate, ρ', is significant enough so that we ought to "rewrite our textbooks" (p. 116). Preliminary empirical evidence is persuasive.

Pindyck (1992) analyzed the decision to start or continue building a nuclear power plant in the early 1980s, a period of considerable uncertainty about construction and operating costs in the utilities business. Using cross-sectional time-series data he explained, *ex post*, how discontinuing construction on plants that were 40 percent complete was a reasonable economic decision for utility companies, due to uncertainty about costs. There were two sources of cost volatility: uncertainty about how long construction would take (up to ten years) and about the prices of building materials, as well as uncertainty about the structural requirements for new facilities to meet escalating government safety regulations which followed an accident at the Three Mile Island nuclear power facility.

Brennan and Schwartz (1985) observed historical data on copper prices, documenting annual fluctuations of 25 to 40 percent. Because of this volatility, they showed why a copper price significantly above the break-even level is required for investors to favorably consider a proposal to open a mine. Similarly, when copper prices drop, they demonstrated how inertia is optimal in decisions about closing

mines. They used the investment under irreversibility and uncertainty framework to quantify how much variability in important investment parameters affects investment timing.

Dixit (1989) tested the hypothesis that exchange rate volatility makes a difference in import flows and in patterns of investment. For export projects whose profits vary according to exchange rates, Dixit cited a coefficient of variation of 10 percent over one year. He presented numerical results to corroborate his observation that "foreign firms that invested in U.S. markets when the dollar was high do not abandon their sunk investments when the dollar falls" (Dixit, 1989, p. 205).

These three empirical studies offer evidence that uncertainty and irreversibility cause investment behavior to be more sluggish than standard theory would predict. Pindyck (1991a) remarked, however, that the notions of irreversibility and uncertainty "seem to be missing from most empirical work on investment" (p. 137), and that "the gap here between theory and empiricism is somewhat disturbing" (p. 140). The conceptual framework for using contingent claims analysis to account for the effects of uncertainty and irreversibility on investment behavior has been developed recently. To assure continued progress in this area, Pindyck recommended that "determining the importance of these factors should be a research priority" (1991a, p. 140).

Taking on this research priority--empirical analysis to measure the importance of uncertainty and irreversibility in explaining investment behavior--is a two-pronged challenge. First is the possibility of contributing to incremental progress in economic theory-building by determining whether the strength of the empirical results is

sufficient to justify continued development of this conceptual framework. The other dimension is its potential for improving applied economic analysis, by adding to the existing conceptual framework for predicting technology adoption under uncertainty and irreversibility. The first half of this final section is a concise statement of the model for predicting investment under irreversibility and uncertainty. The second half lists research hypotheses; these are tested in Chapter Five, "Results."

Rudiments of the Conceptual Framework

The fundamental elements of this conceptual framework for empirical analysis of investment decision making are summarized in Equations (3-15) and (3-16), as portrayed in Figure 3-3. Its primary goal is to identify the level of expected revenues from the project where the opportunity cost of waiting exceeds value of waiting and it becomes optimal to initiate the investment. This occurs at H, a unique threshold of expected revenues from the project which triggers investment. Another objective of the analysis is to quantify the effect of uncertainty and irreversibility on investment behavior. This is accomplished by contrasting the investment trigger, H, with the level of revenues, M, the threshold for recommending investment derived from the standard present value criterion. This comparison generates an estimate of the effect of irreversibility and uncertainty on investment behavior.

To formulate an optimal investment decision rule under irreversibility and uncertainty requires data on four observable parameters: the risk-adjusted discount rate (ρ), the investment cost (K), the expected annualized returns from the investment

(R), and the variance (σ^2) on expected returns. The risk-adjusted discount rate is an estimate of the opportunity cost of capital, or what the resources invested in a particular project could earn in their next best use. This discount rate is a hurdle rate, which may be higher or lower than the market rate of return on similar projects. The investment cost associated with initiating the project can be observed directly in the market, by watching what other investors pay to enter similar investment projects.

Estimates of annualized net returns from the project and of the variance on expected returns requires both information and judgment.[14] These estimates require collecting and evaluating the best possible information on the expected flow of costs and revenues from the project. To capture the effects of uncertainty, it is necessary to account for factors likely to cause fluctuations in returns to the investment, including production levels, costs, and prices. Beyond what is required to apply the present value criterion, an estimate of the variance on expected returns is the only additional data needed to analyze investment under uncertainty and irreversibility.

In summary, with estimates of four investment parameters--R, σ^2, K and ρ--it is possible to calculate the level of expected returns required to trigger investment, and to contrast this level with the present-value decision rule. The optimal investment trigger satisfies Equation (3-16), and the multiplier $\beta/(\beta - 1)$ quantifies how much the

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[14]These estimates are often based on historical data. If, however, the investment project involves a new technology which has not been tested commercially, or a product which has not been widely marketed, then sufficient historical data do not exist. Experimental data and perceptions form the basis for estimates of net returns and its variance. Sensitivity analysis is recommended, whatever the source of estimates on variability on returns.

effects of uncertainty and irreversibility raise the hurdle rate (equivalently, the difference ρ' minus ρ). The optimal investment trigger and the multiplier $\beta/(\beta - 1)$ are both reduced-form equations. Respectively, these reduced-form equations signal to an investor when it is optimal to invest and indicate the effect of uncertainty and irreversibility on optimal decision making.

In the next chapter, the data required to fit these reduced form equations are displayed (estimates of R, σ^2, K, and ρ) pertaining to the decision whether and when to invest in a free stall dairy facility in Texas. Simulation techniques are employed to estimate the volatility of expected net returns and of the investment cost. These procedures are also explained in the next chapter, "Data and Methods."

Research Hypotheses

Five research hypotheses are tested in the empirical analysis of the decision whether and when to invest in free stall dairy facilities.

First, an investment in a free stall dairy facility is characterized by uncertainty and irreversibility. The effect of uncertainty and irreversibility on investing is reflected in a modified hurdle rate. This modified hurdle, ρ' is hypothesized to be greater than the discount rate, ρ, employed as a decision criterion in economic analysis based on present-value comparisons.

Second, when dairy producers convert to free stall operations from conventional open lot facilities, the variance statistic measures the effect of anticipated changes in the variability of milk production and in operating costs on expected

returns from the investment. Using higher estimates of the variance on expected returns from investing in the investment analysis is hypothesized to increase the level of the modified hurdle rate and of the optimal investment trigger. The overall value of the opportunity to invest is hypothesized to increase as uncertainty about expected returns increases.

Third, the discount rate used to evaluate a free stall investment project makes a difference in the level of the optimal investment trigger. A higher discount rate applied to analysis of a free stall investment opportunity is hypothesized to raise the modified hurdle rate, to lower the optimal investment trigger, and to lower the overall value of the investment opportunity. Conversely, a lower discount rate applied to analysis of a free stall investment opportunity is hypothesized to lower the modified hurdle rate, to raise the optimal investment trigger, and to raise the overall value of the investment opportunity.

Fourth, uncertainty exists about the cost of installing a free stall facility, due particularly to evolving standards for environmental compliance. A higher variance in the costs of investing is hypothesized to correspond with a higher optimal investment trigger.

Fifth, whether the future costs of investing are expected to go up or down was hypothesized to make a difference in optimal investment behavior. If the cost of investing is expected to increase in future periods, then an investor is hypothesized to be less likely to invest in the future, in accord with optimal investment criteria. If she invests at all she is hypothesized to be more likely to invest now than later. If the

cost of investing is expected to fall in future periods, then an investor is hypothesized to be more likely to invest in the future than in the current period. Immediately, the optimal investment behavior is hypothesized to be waiting. As savings in investment costs are observed in future periods, the hypothesized optimal investment behavior is monitoring expected returns carefully in order to invest just when the value of waiting and the opportunity costs of foregone revenues from investing are equal.

In Chapter Five, "Results," these five hypotheses will be tested and accepted or rejected, based on data pertaining to an investment in a free stall dairy facility. The data and methods required for hypothesis testing are described in the next chapter, "Data and Methods."

CHAPTER 4
DATA AND METHODS

Currently in Texas, free stall dairy facilities are few and far between. Among 2050 dairies (Texas Milk Market Administrator), there are approximately two dozen free stall operations in Texas (Pagano et al., 1993b). About half of these have been built within the past five years for large commercial herds. In November, 1992, a building contractor in Texas, remarked that "free stall operations are beginning to appear . . . due to water and waste concerns. I think in the next two years we're going to see a lot of free stalls down here because of that" (Hallady, 1992b).

While only a few Texas producers are currently dairying in free stalls, many others are weighing the option of converting from their current open lot facilities to free stall barns. The investment is sizeable, approximately $950 per cow (Pagano et al., 1993b). Both uncertainty and irreversibility impinge on optimal investment decision criteria. The objective of this chapter is to present economic data for analyzing a prospective investment in a free stall dairy facility, and to describe simulation methods for estimating the parameters required to specify optimal investment decision rules under irreversibility and uncertainty.

Because free stall dairying in the South is a recent phenomenon, only sparse cross-sectional time-series data exist for estimating the anticipated net returns from

investments in improved dairy housing. To forecast expected economic performance on free stall dairies using econometric methods would require a large sample in order to account for intra-farm and inter-farm variability due to random price changes and environmental effects, as well as management and economies of size.

As an alternative, a profile of prototypical costs and returns associated with free stall dairying was developed from interviews with dairy producers in Texas, Florida and California (Pagano et al., 1992b, 1992c, 1993a, 1993b) and from published literature on dairy management (Pagano et al., 1992a, 1993b). This prototypical dairy profile was designed as baseline data for an *ex ante* analysis of whether and when dairy producers in central Texas are likely to invest in free stall facilities. This chapter summarizes the profile, and reports results from applying simulation techniques to account for variability in milk production levels and fluctuations in feed costs on the economic performance of a prototypical free stall dairy. The basis for specifying the parameters of the simulation model was expert opinion from dairy producers and from dairy researchers; technical coefficients are from their notions of ranges within which costs and performance are likely to occur.

An important component of this economic profile is an estimate of the costs associated with pollution prevention and a description of how these costs are likely to evolve over time. Compliance with environmental regulations has become a large and increasing cost of dairy production in Texas. The estimated cost of installing a waste management system on a conventional open lot dairy in Texas is $184 per cow, and annual operating costs are approximately $75 per cow (Lovell et al., 1992). Future

compliance costs are uncertain, due to uneven enforcement of existing regulations, as well as continuing debate on air and water regulations at the federal and state levels.

Waste management systems on free stall dairies are equipped with flush systems which are more efficient and reliable than conventional waste management systems on open lot dairies. Technical efficiency can partially or totally offset the cost of building a free stall barn: cows in free stalls are comfortable, and more comfortable cows produce more milk and cost less to feed (per hundredweight of milk produced). Cost-effective free stall dairying, however, is contingent on good management; special attention to waste management, cow logistical patterns, feet and leg problems, and reproduction is necessary. The data and analysis in this chapter depict the level of economic performance required for free stall dairying to be cost-effective; this profile demonstrates what it takes for gains in technical efficiency to offset the investment cost.

This chapter is divided into four sections. In the first section, a profile of the costs and returns associated with free stall dairying is presented, and the investment project is assessed using a decision rule based on present-value calculations. To demonstrate how risk affects optimal investment criteria, the results of simulation modeling are reported in the second section. The third section lays the groundwork for further investigation of the effect on optimal investment behavior of uncertainty and irreversibility. A method is demonstrated for estimating the parameters of a random process using results from simulation modeling. A method is discussed for estimating the trend and the variance on expected investment returns, and similar

techniques are described for estimating the variance on the expected cost of investing in free stall facilities due to evolving standards of environmental compliance.

A Comparative Profile of Dairy Costs and Returns

This section outlines the costs and returns associated with a conventional open lot dairy operation in central Texas, compared with the anticipated economic performance from converting that dairy to a free stall facility. The prototypical 1200-cow dairy described in this profile has been in operation for five to seven years (it was established between 1985 and 1987). For detailed discussion of data and assumptions used to develop this profile, please refer to Pagano et al., 1993b.

The first topic in this section is a discussion of the environmental compliance requirements for dairy waste management systems in Texas. Second, an estimate of the cost of constructing a new free stall barn and accompanying waste management system is presented. Next is a description of how open lot dairies and free stall dairies are similar, and how they differ, from an economic standpoint. The anticipated returns to equity, management, and risk for the two prototypical dairy operations are compared. Given this comparison, the final subject in this section is an assessment of the investment option using a present-value decision criterion.

Environmental Compliance on Open Lot and Free Stall Dairies

The decision whether to invest in a free stall facility is not a choice to make a transition from inadequate waste management practices to compliance. The

prototypical open lot dairy already holds an operating permit from the Texas Water Commission (TWC), having invested approximately $230,000 in a waste management system (excluding land) in order to meet the dairy pollution control regulations established in Texas in the late 1980s (Pagano et al., 1993b).

From 1989 through 1993, complying with TWC requirements for dairy waste management involves building a system of anaerobic lagoons for waste water storage with capacity sufficient to hold all surface water runoff from a 24-hour, 25-year flood event. Site-specific best management practices for scraping corrals and for spreading manure on cropland are outlined in each dairy's operating permit. The technology-based standards enforced by the TWC are consistent with the National Pollution Discharge Elimination System (NPDES) permit pertaining to concentrated animal feeding operations (CAFOs), originally outlined in the 1972 Clean Water Act and recently resurrected in Texas ("National...", 1992, 1993).

From an environmental compliance standpoint, there are two major advantages from a free stall facility. First, consumptive use of water is reduced by approximately 50 percent (Sweeten et al., 1983). Second, waste water is channeled into a flush system which handles approximately 95 percent of all manure generated. In contrast, on conventional open lot facilities, the standard operating procedure is to scrape manure from corrals and apply it directly to cropland. Free stall flush systems are equipped with solid separators which remove a large proportion of manure fiber and nutrients from waste water and produce a by-product ideal for composting (Moore, 1989). Nutrients from composted manure applied to cropland are available

to plants, but are not likely to contaminate ground and surface water (Rynk, 1989). Alternatively, recycled solids are often used as bedding in free stall barns (McFarland, 1992; Carroll and Jasper, 1978).

This analysis focuses on the choice of whether and when to expand to a full free stall barn, though other technological innovations in dairy housing in the South are also important. The cost of building a covered feed lane with a flush system is about half the cost of a free stall barn; many dairy producers in the South, therefore, are opting to build covered feed lanes rather than full free stall barns (Pagano et al., 1993b). Which technology is appropriate--and which is most cost-effective--depends on site-specific considerations such as humidity, rainfall, wind, and soil type (the propensity for dairy corrals to be muddy).

Estimated Investment Costs for a Free Stall Facility

A prototypical candidate for an investment in a free stall facility in central Texas is currently operating a conventional 1200-cow open lot dairy on 400 acres. As a rule of thumb, open lot facilities in semi-arid[1] places--where lots are scraped and runoff and wash water is stored in lagoons--require approximately six irrigated acres per 100 cows; a free stall facility with a flush system requires 50 acres per 100 cows (Armstrong, 1992). Free stall dairies often recycle flush water several times before using it for irrigation. As part of setting up a free stall waste management system, 200 acres of irrigated cropland are required, in addition to the 400 acres

[1]Average annual rainfall in Erath County, Texas, is 28 inches.

owned by the prototypical dairy. Constructing additional waste water storage capacity (that is, lagoons) for the free stall facility costs an estimated $78,597 (Schwart and Lacewell, 1992). Expenses related to the waste management system account for approximately one-third of the projected cost of a new free stall facility. Housing is constructed for the milking herd only (1000 cows); existing open lot housing and pasture are used to house dry cows (200 cows). Estimated investment costs for a free stall facility are summarized in Table 4-1.

Table 4-1: Cost Estimate for a 1000-Cow Free Stall Facility

ITEM	COST PER UNIT	COST PER STALL	TOTAL
Site leveling and shaping	$2250 per acre		$16,787
Fencing - exercise lots	$1.75/linear foot		$2,725
Free stall housing		$550 per stall	$550,000
Solid separator with concrete pads for compost	$30,000		$30,000
Waste management system:			$78,597
Settling basin	$5,537		
Retention lagoon	$51,995		
Storage lagoon	$14,895		
Pipe	$6,170		
Center-pivot irrigation rig	$27,500		$27,500
Irrigation pump	$18,500		$18,500
Equipment & cost over-runs	Nine percent of total cost		$85,891
Additional acreage for irrigation - 200 acres	$700 per acre		$140,000
TOTAL COST		$950 per stall	$950,000

Source: Pagano et al., 1993b.

A common source of financing for capital investments on large dairies is loans from insurance companies. Borrowed capital from insurance companies is repaid with six to eight percent interest over fifteen years. The prototypical free stall investment loan is $800,000 ($950,000, less a $150,000 down payment); the annual cost of repayment under this lending scenario are $93,464 (Pagano et al., 1993b).

Comparing Profiles of Open Lot and Free Stall Dairies

Milk sales and feed costs are the major differences in costs and returns between free stall dairies and open lot dairies (Pagano et al., 1993b). Average milk production on a free stall dairy is a rolling herd average of 21,105 pounds, annual tank sales are approximately 245,662 hundredweight. Average milk production on an open lot dairy is a rolling herd average of 19,530 pounds, annual tank sales are approximately 227,329 hundredweight. The central Texas milk price used in this investment analysis is $12 per hundredweight, 12 percent below a 36-month average (1990 to 1992) of $13.63 per hundredweight (Texas Milk Market Administrator).

Feed costs on an open lot dairy average $5.28 per hundredweight of milk produced, contrasted with feed costs on a free stall dairy averaging $5.19 per hundredweight of milk produced (Pagano et al., 1993b). Improved cow comfort enhances dairy feed efficiency.[2] Under stressful conditions, at least 1.5 pounds of dry matter consumption is required for each pound of milk produced; under more

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[2]Feed efficiency includes improvement in bovine physiological performance in converting feed to milk due to comfortable and consistent conditions in the feeding and loafing areas, plus reductions in wasted feed because the feed lane is covered.

favorable conditions, feed requirements drop to 1.1 pounds of dry matter consumed per pound of milk produced. Wasted feed in free stall barns is less than when cows are fed outdoors on open lots. The range of expected improvement in feed efficiency from moving into free stall facilities is between four and twenty percent; in this profile, the prototypical dairy improves feed efficiency by six percent.

A summary of costs and returns for a prototypical free stall dairy is displayed in Table 4-2, and a summary for a prototypical open lot dairy is given in Table 4-3.

Table 4-2: Anticipated Annual Costs and Returns for a Free Stall Dairy

	PER-COW COST OR REVENUE	PER-CWT COST OR REVENUE	ANNUAL TOTAL	GRAND TOTALS
REVENUES				
Milk sales	$2457 per cow	$12 per hundredweight	$2,947,946	
Animal sales*	$271 per cow	$1.32 per hundredweight	$324,800	
TOTAL REVENUES	$2728 per cow	$13.32 per hundredweight		$3,272,746
EXPENSES				
Animal purchases*	$400 per cow	$1.95 per hundredweight	$480,200	
Feed	$1095 per cow	$5.35 per hundredweight	$1,314,419	
Labor*	$168 per cow	$0.82 per hundredweight	$201,520	
Other operating costs	$583 per cow	$2.85 per hundredweight	$699,666	
Debt service* (mortgage and operating loan only)	$270 per cow	$1.32 per hundredweight	$324,345	
TOTAL EXPENSES	$2517 per cow	$12.29 per hundredweight		$3,020,151
RETURNS TO EQUITY, MANAGEMENT, AND RISK (without free stall investment costs)	$211 per cow	$1.03 per hundredweight		$252,595

Source: Pagano et al., 1993b.

Note: Asterisks indicate items which are the same in Tables 4-2 and 4-3. Cost and revenue calculations in the third column are based the quantity of milk sold.

The gross returns to equity, management and risk on a free stall dairy, reported on the bottom line in Table 4-2, do not include the estimated annual cost of the investment in the new facility, $93,464. Deducting this cost, anticipated net returns from the free stall dairy are $159,131. The difference in anticipated net returns to equity, management and risk between an open lot dairy and a free stall dairy is $53,367. This is the anticipated annual return from an investment in a free stall facility; it represents what a dairy producer would expect to earn from free stall dairying, over and above previous earnings from open lot dairying (Table 4-3).

Table 4-3: Anticipated Annual Costs and Returns for an Open Lot Dairy

	PER-COW COST OR REVENUE	PER-CWT COST OR REVENUE	ANNUAL TOTAL	GRAND TOTALS
REVENUES				
Milk sales	$2462 per cow	$12 per hundredweight	$2,727,950	
Animal sales*	$271 per cow	$1.43 per hundredweight	$324,800	
TOTAL REVENUES	$2733 per cow	$13.43 per hundredweight		$3,052,750
EXPENSES				
Animal purchases*	$400 per cow	$2.11 per hundredweight	$480,200	
Feed	$1031 per cow	$5.44 per hundredweight	$1,237,421	
Labor*	$168 per cow	$0.89 per hundredweight	$201,520	
Other operating costs	$586 per cow	$3.09 per hundredweight	$703,500	
Debt service* (mortgage and operating loan only)	$270 per cow	$1.43 per hundredweight	$324,345	
TOTAL EXPENSES	$2,546 per cow	$12.96 per hundredweight		$2,946,987
RETURNS TO EQUITY, MANAGEMENT, AND RISK	$88 per cow	$0.47 per hundredweight		$105,764

Source: Pagano et al., 1993b.

Note: Asterisks indicate items which are the same in Tables 4-2 and 4-3. Cost and revenue calculations in the third column are based the quantity of milk sold.

Several aspects of dairying are not affected by moving to a free stall facility. Animal sales and purchase patterns are similar on open lot and free stall dairies (Pagano et al., 1993b). On average, 83 percent of the cows in the herd are in milk. The average calving interval is 13.6 months; the annual cull rate is 33 percent including a three percent death loss. The prototypical dairy buys springers (cows ready to enter the milking herd) and five bulls per year. Most breeding is done with artificial insemination. The dairy sells cull cows and all its calves. They buy springers rather than raising replacements. Based on these figures, the average annual animal sales from a 1200-cow dairy are $324,800, just short of offsetting average annual animal purchases of $480,200.

Labor costs on prototypical open lot and free stall dairies are similar (Pagano et al., 1993b). Although there are differences in the allocation of tasks on the two types of facilities, the size of the work forces on 1200-cow dairies in Texas are about the same: large dairies in central Texas require one employee per 100 cows. Dairy wages average $1300 per month plus social security benefits.

Most large dairies are leveraged. In most cases, investing in a new facility means taking on a heavier debt load while continuing to pay off existing loans. The initial investment required to establish a prototypical 1200-cow dairy in central Texas in 1987 was approximately $2,790,000 for cows, buildings and lots (including milking equipment), land (400 acres), feeding equipment, and a waste management system (Pagano et al., 1993b). Generally speaking, dairymen hold a 45 percent equity share in their dairies and 55 percent is borrowed capital (an estimated $1,534,000). Two-

thirds of a prototypical dairy's debt is a mortgage, the remainder is an operating loan. Annual financing payments on this 1200-cow dairy are $324,345.

There are three differences in operating costs[3] between the two prototypical dairies. First, a fee covering milk hauling charges, cooperative membership, and promotional fees is assessed according to the quantity of milk the dairy sells; in central Texas, the fee is $1.10 per hundredweight sold. Free stall dairies sell more milk than open lot dairies and thus pay a larger amount for combined hauling, cooperative, and promotional fee charges. Second, open lot dairies have larger corrals than free stall dairies. They pay $18 per cow per year to have their corrals scraped and manure hauled, in contrast with free stall dairy producers who pay an estimated $3 per cow per year for lot maintenance. Third, conventional open lot facilities in central Texas spend $6000 per year to control flies during the five summer months; this service is not used on free stall dairies currently operating in central Texas.

In summary, four factors contribute to net positive anticipated returns from an investment in a free stall dairy facility (Pagano et al., 1993b). First, the prototypical dairy anticipates producing eight percent more milk after converting to a free stall operation, an increase of 18,333 hundredweight. Second, the prototypical dairy saves $18,000 per year in corral-scraping and manure-hauling costs, plus a free stall

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[3]Operating costs include milking supplies, veterinary services, breeding, utilities, herd testing (Dairy Herd Improvement Assessment services), fuel, repairs, memberships, permit fees, taxes, legal services, accounting services, and insurance. For a detailed breakdown of these costs, please refer to Pagano et al., 1993b.

operation has no expenditures for fly control. These gains are offset by anticipated higher milk hauling costs, the third factor, and finally by higher feed costs. Though feed efficiency improves by six percent on a free stall dairy, milk production increases by approximately 18,333 hundredweight after the new facility is installed. To produce this additional milk requires a net increase in feed consumption.

Overall, the change in anticipated returns to equity, management and risk due to converting from an open lot dairy into a free stall operation is \$146,831, less the estimated annual cost of the investment, \$93,464. The anticipated overall economic returns from an investment in a new free stall facility, including a waste management system, is \$53,367 (Table 4-4).

Table 4-4: Anticipated Annual Net Returns from a Free Stall Investment

	Net Change	Total Change
Additional Revenues and Savings:		
Net increase in milk sales	\$219,996	
Net savings for lot maintenance and fly control	\$24,000	
Additional Costs:		
Net increase in milk hauling fees	less \$20,166	
Net increase in feed costs	less \$76,999	
GROSS CHANGE IN RETURNS TO EQUITY, MANAGEMENT, AND RISK		\$146,831
Less the cost of the free stall facility		less \$93,464
NET CHANGE IN RETURNS TO EQUITY, MANAGEMENT, AND RISK		\$53,367

The Present Value of a Free Stall Investment

The standard economic criterion for evaluating an investment opportunity is to verify that the present value of the anticipated net returns from the investment is positive. For the present-value calculation, an estimated historical real rate of return from agricultural investments of three percent (Moss et al., 1987) was employed as the discount rate. The pay-out period for the loan on the free stall facility and its expected productive life were assumed to be the same: they were estimated at fifteen years. The present value of the anticipated annual net returns from the free stall investment of $53,367 is $637,092. The present value is positive; thus, when evaluated using conventional economic criterion, the assessment of this free stall investment project is favorable.

Analyzing the Free Stall Investment Under Risk

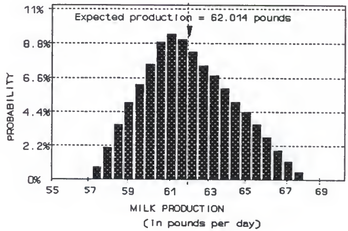
Standard economic analysis based on a present-value decision rule fails to account explicitly for uncertainty about the determinants of the returns from an investment. The second section of this chapter reports the results of simulation modeling which shows the effect of risk on the free stall investment analysis. The first topic in this section is a description of the parameters of the free stall investment analysis likely to vary--and to vary differently--before and after the proposed change in facilities. Results of simulation modeling are reported. This section closes with a discussion on modifying investment decision rules to take account of simulation-based risk information.

Uncertain Parameters in the Investment Analysis

A simulation model was developed using @RISK computer software (Palisade Corporation, 1992). The objective of the modeling was to depict the key differences between the economic performance of an existing 1200-cow dairy and performance of the same dairy after installing a free stall facility. The two most important determinants of economic returns from dairying are milk sales[4] and feed costs. Milk production levels and feed costs were modeled as stochastic in the baseline simulation.

Milk production patterns are expected to differ before and after a free stall barn is built. Average milk production on an open lot dairy is 62 pounds per cow per day (Pagano et al., 1993b); expected production is depicted in Figure 4-1,

Figure 4-1: Expected Milk Production on a Prototypical Open Lot Dairy

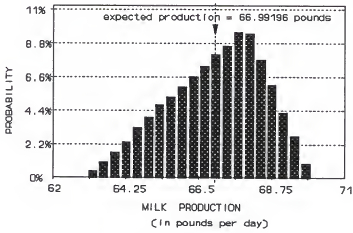


[4]Although both milk price and milk production levels make a difference in total revenues from milk sales, fluctuation in milk prices is outside the scope of this analysis. Whether or not the dairy invests in a free stall facility, milk prices have the same effect on overall variability in milk revenues.

representing simulation results from 15,000 Monte Carlo iterations. Due to stress from heat and humidity in the summer, and from wind and mud in the winter, milk production varies from 57 and 68 pounds per cow per day. A triangular distribution was used to model milk production on an open lot dairy: the most likely observation was 61 pounds per cow per day; the low and high endpoints of the distribution were 57 and 68 pounds per cow per day, respectively; and the expected value was 62 pounds per cow per day.

Expected milk production on a prototypical free stall dairy is both higher and less variable than on a conventional open lot dairy. Average free stall dairy milk production in Texas is 67 to 68 pounds per cow per day (Pagano et al., 1993b). A triangular distribution was used to model milk production on a free stall dairy: the most likely observation was 68 pounds per cow per day; the low and high endpoints were 63 and 70 pounds per cow per day, respectively; and the expected value was 67 pounds per cow per day (Figure 4-2), based on 15,000 Monte Carlo iterations.

Figure 4-2: Expected Milk Production on a Prototypical Free Stall Dairy



Feed costs are the largest operating expense on a dairy, amounting to approximately half of milk sales. Feed costs fluctuate over time, and the cost per hundredweight of feeding cows plays an important role in determining the difference between returns from dairying with or without a free stall facility. Texas dairy producers buy most of their feed, rather than farming themselves. The cost of purchased feed varies due to exogenously determined factors--volatility in feed prices, for example--and also due to factors endogenous to the dairy, such as seasonal differences in cow freshening patterns and changes in management (Pagano et al., 1993b). Feed cost was depicted as normally distributed, with a standard deviation of ten percent of the expected cost of feed per hundredweight of milk produced. Expected feed costs on a free stall were $5.19 per hundredweight of milk produced with a standard deviation of 0.519 (Figure 4-3); the expected feed cost on an open lot dairy was $5.28 per hundredweight of milk produced with a standard deviation of 0.528 (Figure 4-4). Simulation results are based on 15,000 Monte Carlo draws.

Figure 4-3: Expected Feed Costs on an Open Lot Dairy

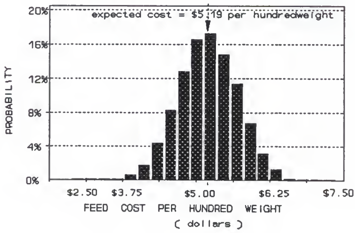
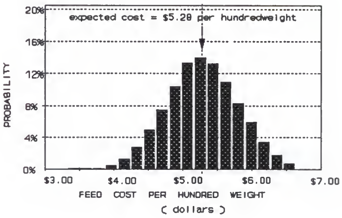


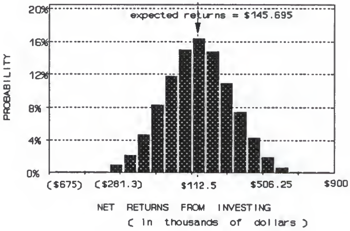
Figure 4-4: Expected Feed Costs on a Free Stall Dairy



Modeling Milk Production and Feed Costs as Stochastic

Results of a simulation model with milk production and feed costs as random variables indicated that the expected value of the change in returns before and after the free stall investment, net of the investment cost, was $52,231. The expected net increase in returns to equity, management and risk from installing a free stall investment is sufficient to cover the investment cost an estimated 61 percent of the time. For risk-averse decision makers, it is more significant that 39 percent of the time the annual payment cannot be paid from the expected returns from investing. The highest expected change in net returns from investing in a free stall facility was earnings of $801,495; the lowest expected change was a loss of $637,731. The simulated distribution of expected returns to equity, management and risk, based on simulation results from 15,000 Monte Carlo samples, is displayed in Figure 4-5.

Figure 4-5: Expected Economic Returns from a Free Stall Investment



Implications of Risk Results for Investment Decision Making

These simulation results highlight the role of risk in investment decision making. Though the present value of expected returns from the investment was positive, this risk assessment shows a wide range of potential present values. Since the confidence interval on the anticipated present value is large, risk preferences make a difference in choosing an investment decision rule. A risk-averse decision maker is likely to consider modifying the present-value decision rule--which recommended the investment--in light of expected returns being positive only 61 percent of the time.

Guidelines for using risk analysis to improve farm management decision making are available (Anderson et al., 1977; Barry, 1984). Making an appropriate adjustment to take account of risk information, however, is a matter of individual judgment. It depends on risk preferences. When there is a wide spread around a

statistic calculated as an investment criterion, one common-sense tactic for adjusting the investment decision rule is to collect more information in order to narrow the confidence interval. That implies waiting to invest. The next section of this chapter outlines techniques for estimating statistics required to estimate the value of waiting--that is, the value of postponing the decision whether to invest.

Estimating the Parameters of a Random Process

In the conceptual framework for analyzing investment behavior under irreversibility and uncertainty (Pindyck, 1991b; Dixit, 1992b), expected returns from an investment are modeled as a geometric Brownian motion process, where the parameters defining the time path of expected returns are its trend (μ) and its variance (σ^2). In this section, a method is demonstrated for estimating the trend and the variance of a random process using results from simulation modeling. The first topic is a description of the technique for estimating the variance and the trend of expected net returns from an investment. Then similar methods are described for estimating statistics which also account for anticipated changes in the cost of investing.

Techniques for Estimating Expected Returns and Its Variance

If cross-sectional time-series data are available, then the trend and the variance on expected investment returns are estimated by fitting a regression from historical data. To conduct *ex ante* analysis of an investment opportunity, an alternative is to use simulation methods to estimate these parameters. The technique requires creating

a time series--by estimating the expected returns from the investment in multiple time periods, using a series of different draws from the same distribution--in order to forecast the anticipated performance of an investment opportunity over time. The sequence of outcomes is simulated over numerous iterations, and parameters of the random process are estimated from the simulation data.

This technique hinges on the same insight exploited by Cox, Ross and Rubinstein (1979): that, in the limit, a discrete approximation to a geometric Brownian motion process converges to the expected value of a geometric Brownian motion variate. To describe the path of a random process over time using results from simulation modeling, it is possible to estimate the parameters of the path of the random variable by measuring the movements which occur in an infinitesimally-small, discrete interval over numerous iterations of a simulation model. This is the same as estimating a difference equation, measuring the change which occurs in the increment of time from a starting point (t) to the next instant ($t+1$). To calculate statistics from simulation data, these estimated differences are summed, and then the total is divided by the number of iterations over which the average is being calculated.

Let V equal the value of the opportunity to invest (the sum of both the value of investing and the value of waiting). The value of the opportunity is modeled as a geometric Brownian motion process:

$$\frac{dV}{V} = \mu dt + \sigma^2 dz \ . \tag{4-1}$$

Note that

$$\frac{d(\ln X)}{dt} = \frac{1}{X}\frac{\partial X}{\partial t} \approx \frac{\Delta X}{X}, \tag{4-2}$$

where $\partial X/\partial t \approx \Delta X$. Using this result,

$$\frac{dV}{V} = \frac{\frac{\Delta V}{\Delta t}}{V} = \frac{1}{V} * \frac{\Delta V}{\Delta t} = \frac{\Delta(\ln V)}{\Delta t}. \tag{4-3}$$

By definition,

$$\Delta(\ln V_j) \equiv \ln(V_t) - \ln(V_{t+1}), \tag{4-4}$$

where j denotes the size of the sample over which this difference is calculated. The net present value of the investment in a given time period, t, and an instant later, at $t+1$, are defined, respectively, as

$$NPV_t = \sum_{i=0}^{n} \frac{R_{t+i}}{(1 + \rho)^i} \tag{4-5}$$

and

$$NPV_{t+1} = \sum_{i=1}^{n+1} \frac{R_{t+i}}{(1 + \rho)^{i-1}}. \tag{4-6}$$

The investment is productive over n time periods. The expected net returns from the investment each year is R. The discount rate used in the present-value calculation is ρ. The standard present-value investment criterion defines a minimum threshold for investing, where $NPV_t \geq K$. The present value of expected returns from investing must exceed the sunk cost (K) of initiating the investment.

The value of the opportunity to invest in perpetuity is

$$V_t = \frac{\left[\dfrac{\rho}{1-\left(\dfrac{1}{(1+\rho)^{n-t}}\right)} NPV_t\right]}{\rho} . \tag{4-7}$$

A moment later, its value is

$$V_{t+1} = \frac{\left[\dfrac{\rho}{1-\left(\dfrac{1}{(1+\rho)^{n-t-1}}\right)} NPV_{t+1}\right]}{\rho} . \tag{4-8}$$

The numerator of Equations (4-7) and (4-8) is the formula for the annuity required to generate a stream of benefits equivalent to the present value of the investment. Dividing this annuity value by the discount rate converts it to the present value of an infinite stream of benefits. This result hinges on the assumption that at the end of n time periods, the productivity of the investment can be renewed for another n time periods by another capital influx of the amount K. An infinite repetition of this process maintains a stream of investment returns in perpetuity.

The difference between the natural logarithm of V_t and V_{t+1} (Equation 4-4) is a discrete estimate of the change in the value of an investment opportunity, an estimate of an increment of a geometric Brownian motion process. To replicate a range of possible outcomes from a risky investment opportunity using simulation methods requires several iterations. In each iteration, estimating Equations (4-5) and (4-6) requires n and $n + 1$ draws, respectively, where each draw represents an observation

of expected annual returns from investing. This process is repeated over j iterations, to estimate the trend (μ) in the geometric Brownian motion process Equation (4-1):

$$\mu_V \approx \frac{1}{N} \sum_{j=1}^{N} [\Delta \ \ln V_j] \ , \tag{4-9}$$

where

$$E[\Delta \ \ln V_j] \rightarrow 0. \tag{4-10}$$

This assumes a stationary process, $\mu_V \Rightarrow 0$. To estimate its variance,

$$\sigma_V^2 \approx \frac{1}{N} \sum_{j=1}^{N} [\Delta \ \ln V_j - \mu_V]^2 \ , \tag{4-11}$$

where

$$E[(\ln \ V_j - \mu_V)^2] > 0 \ . \tag{4-12}$$

The parameters μ_V and σ_V^2, estimated using Equations (4-9) and (4-11) are used to estimate how much it is worth to postpone an investment opportunity, as well as the overall value of an investment opportunity under irreversibility and uncertainty. These procedures are applied to analysis of the decision whether and when to invest in a free stall dairy facility in central Texas in the "Results" chapter.

Methods to Account for Investment Cost Uncertainty

The assumption in the baseline analysis of optimal investment decision making is that the cost of investing is unchanged whether the investment is made now or later. With some investments, due to technological innovation, the anticipated cost of

launching the project drops if the investment is postponed. For example, those investors who delayed purchases of computers during the 1980s enjoyed lower prices, more options, and more powerful technology; waiting to invest meant the opportunity to get more for less. With other investments, due to government regulations or increasing competition from new entrants to the market, postponing means that the anticipated cost of a project increases. In addition, for many investments the final cost is not known with certainty when the investment is initiated. In this section a technique is discussed for calculating revised statistics describing a modified time path of the value of investing--denoted *Z* instead of *V*--which include adjustments to account for uncertainty about the cost of investing in future time periods. These revised statistics are μ_Z and σ^2_Z.

The current cost of initiating an investment project is observable, either from registering the sunk costs paid by recent investors or from soliciting bids by sellers of the investment project. If a project is postponed or if investment is not instantaneous, its cost may change. To model how uncertainty about investment costs in future periods affects optimal investment decision rules, the sunk cost of initiating an investment (*K*) is divided into a time-invariant component (*Q*) and a random component (*I*), such that

$$K = Q + I \, , \tag{4-13}$$

where *I* is modeled as a stochastic variable. In the current period (*t*), when *K* is observable, $E(I) = I$. For future periods ($t = t+1 \ldots n$), $E(I) = I + \varepsilon_I$ where ε_I is the random component of *I*.

For the baseline calculations of *V*--Equations (4-5) to (4-12)--the only stochastic factor influencing optimal timing of an investment was the expected returns from investing. In the calculations of the modified value of investing, *Z*, there is a second stochastic factor, *I*. This modification requires adjusting the basic formula for calculating the optimal investment trigger, $H = \rho' K$. To account for investment costs being uncertain, $H_Z = \rho'[Q + E(I)]$. In the current period, $\varepsilon_I = 0$; thus:

$$NPV'_t = NPV_t = \sum_{i=0}^{n} \left(\frac{R_{t+i}}{(1 + \rho)^i} \right) . \tag{4-14}$$

This formula is the same as for the baseline calculation, Equation (4-6). If, however, the cost of the investment project is uncertain, then *I* is a random variable, modeled as a draw from a normal distribution with mean $E(I) = I$ and variance σ^2_I. To initiate the uncertain investment project, $E(I) = I + \varepsilon_I$, and:

$$NPV'_{t+1} = \sum_{i=1}^{n+1} \left(\frac{R_{t+i}}{(1 + \rho)^{i-1}} \right) - \varepsilon_I , \tag{4-15}$$

where the random portion of sunk costs, ε_I, is stochastic for all future time periods, $t = t+1 \ldots n$, and ε_I is included in the calculation of net returns from investing.

A revised formula for the present value of the cost of investing in perpetuity, with the flexibility to account for uncertainty about the cost of investing, is

$$Z_t = \frac{\left[\dfrac{\rho}{1 - \left(\dfrac{1}{(1 + \rho)^{n-t}} \right)} NPV_t \right]}{\rho} . \tag{4-16}$$

A moment later, when the investment cost becomes uncertain, its value is

$$Z_{t+1} = \frac{\left[\dfrac{\rho}{1 - \left(\dfrac{1}{(1 + \rho)^{n-t-1}} \right)} NPV'_{t+1} \right]}{\rho} . \tag{4-17}$$

The numerators of Equations (4-16) and (4-17) are the calculation for the annual loan payment required to repay the cost of the investment in n time periods (equivalently, the formula for an annuity). Dividing this annuity value by the discount rate converts it to the present value of an infinite stream of benefits in perpetuity. This result hinges on the assumption that at the end of n time periods, the productivity of the investment can be renewed for another n time periods by another capital influx of the amount K. An infinite repetition of this process generates a stream of investment returns in perpetuity.

Recall from Equations (4-1) to (4-4) that

$$\Delta \ln(Z_j) \equiv \ln(Z_t) - \ln(Z_{t+1}) \tag{4-18}$$

where j denotes the number of iterations over which this difference is calculated. This difference is an estimate of an increment of a geometric Brownian motion process representing the time path of the value of the opportunity to invest. To replicate the range of possible outcomes from the investment opportunity using simulation methods requires several iterations. In each iteration, estimating Equations (4-14) and (4-15) requires n and $n + 1$ draws, respectively, where each draw represents an observation of expected annual returns from investing; for

Equation (4-15), each iteration requires $n + 1$ draws of I as well. This process is repeated over j iterations. To estimate the trend in the value of investing under cost uncertainty:

$$\mu_Z \approx \frac{1}{N} \sum_{j=1}^{N} [\Delta \; lnZ_j] \tag{4-19}$$

where

$$E[\Delta lnZ_j] \rightarrow c \; . \tag{4-20}$$

This represents a non-stationary process. To estimate its variance,

$$\sigma_Z^2 \approx \frac{1}{N} \sum_{j=1}^{N} [\Delta lnZ_j - \mu_Z]^2 \; , \tag{4-21}$$

where

$$E[(\ln Z_j - \mu_Z)^2] > 0 \; . \tag{4-22}$$

The parameters μ_Z and σ_Z^2, estimated in Equations (4-19) and (4-21) are used to account for the effect of uncertainty about future costs of investing on optimal investment decision rules. These procedures are applied to an analysis of the decision whether and when to invest in a free stall facility in central Texas in the "Results" chapter.

CHAPTER 5
RESULTS

In this chapter, results of the empirical analysis are reported. Five theoretically-based hypotheses were tested to assess dairy producers' responsiveness to the option to invest in free stall facilities. This technology option has implications both for production efficiency and for environmental compliance.

Financial benefits from increased milk production and lower feed costs are likely to offset the cost of installing a free stall facility. Accordingly, promoting the adoption of technologies like free stalls may be a more cost-effective way to improve environmental compliance on dairies than promoting technologies which have no such cost-offsetting benefits. The magnitude and the timing of cost-offsetting benefits, however, are uncertain; any such benefits are contingent on management as well as factors beyond the control of management. Therefore, appropriate policy prescriptions are not as simple as deciding, for example, how much cost sharing to offer; rather, taking account of the uncertainty associated with free stall investments also makes a difference. The general objective of this presentation of results is *ex ante* forecasting of how uncertainty is likely to affect investment behavior. Empirical results focus on how uncertainty about future environmental compliance costs affects whether and when Texas dairy producers are likely to invest in free stall facilities.

The environmental compliance aspect of free stall dairying poses a particular quandary for Texas dairy producers. Recently they have made major investments--investments with large sunk-cost components--to establish dairies in Texas, many having relocated from other dairy regions. In particular, from 1987 to 1993, many Texas dairy producers made large investments, both financial and personal, to comply with the Texas Water Commission's rules (Leatham et al., 1992). A producer who moved his operation from California to Texas in 1990 summarized his viewpoint:

> My last dying breath is going to be here in Erath County. I've set down here and I'm staying. This is a lifelong operation and I feel I'm a good operator. I'm not doing anything wrong (Terrell, 1992).

His last line pertains to his continuing efforts to comply with environmental rules.

Uncertainty about future dairy waste management requirements in Texas complicates investment decision making. In neighboring states, such as New Mexico, the costs of environmental compliance were, in 1993, lower than in Texas (Brister, 1993a); accordingly, several new dairies were opened in New Mexico in 1993 and some Texas producers are contemplating relocating there. Irreversible investments inhibit flexibility, and, in one producer's words, "Texas dairymen have already made a huge contribution toward protecting the environment" (DeJong, 1993b). An additional irreversible investment--a free stall facility--would further constrain their options to relocate in response to future shifts in comparative advantage, either due to environmental regulations or due to milk pricing or due to differences in feed costs across states (Hallady, 1992a). These considerations enter into investment behavior and, therefore, have implications for environmental policy performance.

The first section in this chapter describes how uncertainty about the returns from an irreversible investment in a free stall facility affects producers' propensity to invest. The second and third sections discuss the results of sensitivity analysis: how changes in the variability of net returns from investing and changes in the discount rate employed in the analysis, respectively, are likely to affect investment behavior. The fourth and fifth sections explore the effect of uncertainty and irreversibility on dairy producers' responsiveness to free stall investment opportunities, particularly uncertain investment costs due to evolving pollution abatement requirements.

A Modified Hurdle Rate

When analyzing an investment opportunity using the conventional present-value criterion, the investment is deemed acceptable if the internal rate of return from investing is above the discount rate (ρ) employed in the analysis. A modified hurdle rate, ρ', includes the effects of irreversibility and uncertainty on optimal investment behavior. For investments with uncertain returns, the modified hurdle rate is calculated by adjusting the discount rate by a multiplier, $\beta/(\beta-1)$, where

$$\beta = \frac{1}{2}\left[1 + \sqrt{1 + \frac{8\rho}{\sigma^2}}\right], \qquad (5\text{-}1)$$

as stated in Equation (3-17). The formula for the modified hurdle rate is

$$\rho' = \frac{\beta}{\beta - 1}\,\rho\,, \qquad (5\text{-}2)$$

as stated in Equation (3-18).

The purpose of the first hypothesis test was to determine the extent to which irreversibility and uncertainty affect investment behavior.

$$\begin{aligned} H_0&: \ \rho = \rho' \\ H_A&: \ \rho < \rho' \end{aligned} \tag{5-3}$$

Under the null hypothesis, uncertainty and irreversibility were hypothesized to have no effect on the hurdle rate. The alternative hypothesis allowed for the possibility that irreversibility and uncertainty raises the hurdle rate. The hypothesis test involved verifying whether or not there was a statistically significant difference between the discount rate employed in a present-value analysis and the modified hurdle rate.

The discount rate (ρ) employed in the analysis of the free stall investment decision was an estimated historical rate of returns from agricultural investments of three percent (Moss et al., 1987). To generate the statistics (μ_V, σ_V^2) required to estimate a modified hurdle rate based on simulation results--as detailed in the previous chapter--five steps were followed. First, an estimate of the expected change in returns due to converting an existing open lot dairy to a free stall facility was calculated (see Table 4-4), with milk production levels and feed costs modeled as stochastic. The second step was to calculate the present value of fifteen separate draws from the distribution of the expected returns from investing, following Equations (4.5) and (4.6). The expected productive life of the investment was assumed to be 15 years ($n = 15$). The third step was to annualize these present value calculations and to calculate the value of investing in perpetuity, stated in Equations (4.7) and (4.8). Following Equation (4.4), the fourth step was to calculate the

difference between the natural logarithms of expected values of V_j for two consecutive time periods, t and $t+1$. The final step was to estimate Equations (4.9) and (4.11) over j iterations.

To calculate a stable estimate of the trend and the variance on the expected returns from investing in a free stall dairy facility, j was set equal to 25,000 iterations.[1] The calculation of the trend and the variance was repeated for 100 separate simulations resetting the seed values for the random number generator for each simulation. Reported statistics were calculated as a simple average of the results from these 100 Monte Carlo samples. The estimated value of the trend in the expected returns from investing was $\mu_V = 0.0002335$ (Appendix A). A student's t-test was conducted to verify that $\mu_V \approx 0$. Formally,

$$\begin{aligned} H_0&: \ \mu_V = 0 \\ H_A&: \ \mu_V \neq 0 \,. \end{aligned} \tag{5-4}$$

The standard deviation of μ_V from 100 estimates of the trend was $\sigma_{\mu V} = 0.001294$ and the t-test statistic was 0.18045 (Appendix A). The result of a two-tailed t-test was to fail to reject the null hypothesis.

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[1]The estimates of the trend and the variance of the expected returns from investing were based on 25,000 iterations (Evans and Savin, 1981, 1984). Each iteration represented a Monte Carlo random draw. The goal was to arrive at a consistent estimator of the population statistic (White, 1983), such that

$$plim\ (x - \mu_V)^2 \ \rightarrow \ \sigma_V^2$$

where

$$\sigma_V^2 = \frac{1}{N} \sum_{i=1}^{N} (x_i - \mu_V) \ \rightarrow \ c \,.$$

The estimated value of the variance on expected returns from investing based on 100 Monte Carlo samples was $\sigma_V^2 = 0.04315$ (Appendix A). Using this estimated variance to adjust the discount rate of three percent used in the analysis, a modified hurdle rate, ρ', was calculated, indicating that an internal rate of return of $\rho' = 6.83$ percent is required for optimal investing. This modified hurdle rate was more than double ($\beta/\beta\text{-}1 = 2.28$) the hurdle rate ($\rho = 3$ percent) required to approve an investment under a present-value criterion. A formal hypothesis test was conducted, as specified in Equation (5-3), to test whether $\rho' > \rho$. The standard deviation of ρ', calculated from the 100 simulation estimates of ρ', was 0.001693 and the resulting t-test statistic was 22.69 (Appendix A). Using a one-tailed test the null hypothesis was rejected.

In summary, uncertainty and irreversibility make a difference in investment behavior. Accounting for uncertainty and irreversibility means that optimal investment timing requires a rate of return from investing more than double the hurdle rate which applies to present-value analysis. If anticipated annual returns from investing were $M \geq \$83,448$,[2] then, optimally, an investor using a present-value decision criterion to consider the free stall investment would go ahead with it. To

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[2]The annuity required to generate \$996,2200 in 15 years (the expected productive life of the investment) at three percent (the expected real rate of return) is \$83,448. The lump sum, Q = \$996,200 is the sum of the \$950,000 estimated cost of the free stall facility plus \$46,200 due to first-year adjustment costs.

First-year adjustment costs, \$46,200, are due to an anticipated increase in the cull rate as dairy cows adjust to the new facility. Normal cull rates are 33 percent; in the first year, most free stall dairy producers experience a 40 percent cull rate (Pagano et al., 1993b).

calculate the optimal trigger, which accounts for irreversibility and uncertainty, the break-even returns from investing are multiplied by the modified hurdle rate, ρ':

$$H = \frac{\beta}{\beta - 1} \rho K \tag{5-5}$$

as stated in Equation (3-16). Thus H = \$190,063 is the trigger level of expected returns from investing which signals the optimal timing for a free stall investment; in other words, for it to be better to invest in a free stall facility than to wait, anticipated returns from investing must be greater than or equal to \$190,063.

Changing the Variance on Returns from Investing

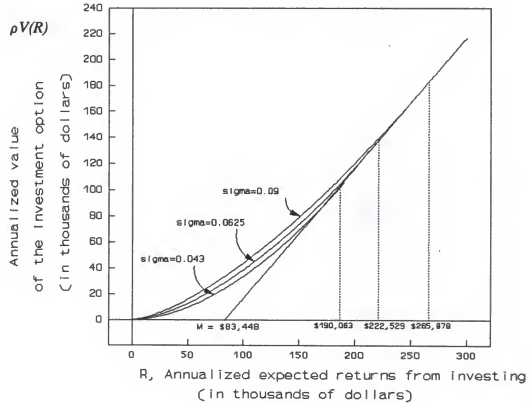
According to Pindyck (1991b), the measures of variability around $\sigma = 0.2$ and $\sigma = 0.3$ are "conservative for many projects; in volatile markets, the standard deviation of annual changes in a project's value can easily exceed 20 or 30 percent" (p. 1123).

The second hypothesis was that raising the variance on expected returns from investing raises the level of the modified hurdle rate and of the optimal investment trigger, ceteris paribus. The overall value of the opportunity to invest increases when uncertainty associated with expected returns increases.

Sensitivity analysis was conducted to demonstrate the effects of changing the variance on expected returns from investing. Three scenarios were analyzed: the case of $\sigma_V^2 = 0.043$ (corresponding with the empirical profile of the free stall investment) was contrasted with $\sigma^2 = 0.0625$ and $\sigma^2 = 0.09$. Results of sensitivity analysis are

graphed in Figure 5-1: the annualized value of the investment option, $\rho V(R)$, is an increasing function of annualized expected returns from investing (R). The discount rate for these calculations was fixed at $\rho = 0.03$ and the sunk cost of the investment was $Q = \$996,200$, where M = \$83,448 (the value of an annuity to yield Q after 15 years at 3 percent).

Figure 5-1: Sensitivity Analysis of the Effects of the Variance on Returns from Investing on the Modified Hurdle Rate



In Figure 5.1, R and $\rho V(R)$ are denominated in annualized values.[3] This presentation is a hybrid of graphs from Pindyck (1991b) and from Dixit (1992b). Pindyck (1991b, p. 1123) displayed results of sensitivity analysis in a graph with normalized present values on both axises. Dixit (1992b, p. 114) used present-value increments for $V(R)$ and annualized values for R; this is the graph displayed in the theory chapter as Figure 3.3.

How Variance Affects Optimal Investment Behavior

The higher the variance, the higher the expected returns from investing required to trigger investment and the higher the value of the option to invest. The value of the investment option is conceptually equivalent to an option price; $V(R)$ is an estimate of optimal willingness to pay for the option. The overall value of the opportunity to invest equals the value of waiting when $R < H$ and equals the value of investing when $R > H$. That is,

$$V(R) = \begin{cases} BR^{\beta} & \text{if } R \leq H \,, \\ R/\rho - K & \text{if } R \geq H \end{cases} \tag{5-6}$$

as stated in Equation (3-15). Pindyck (1991b, p. 1121) supplied a formula for calculating the constant, B, in the formula for the value of waiting:

$$B = \frac{(H - \rho K)}{H^{\beta}} \,. \tag{5-7}$$

At the optimal investment trigger, the sum of the value of waiting plus the annualized

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[3]Figures 5.2, 5.3, and 5.4 also graph R and $\rho V(R)$ as annualized values.

sunk cost of investing are exactly equal to the expected returns to investing. At the optimal investment trigger, H,

$$V(R) + \rho K = R. \tag{5-8}$$

Modified hurdle rates (ρ'), optimal trigger values (H), and the annualized values of the option, $\rho V(H)$, were compared for three levels of variance on expected returns from investing: $\sigma_V^2 = 0.043$ ($\sigma = 0.2$), $\sigma^2 = 0.0625$ ($\sigma = 0.25$), and $\sigma^2 = 0.09$ ($\sigma = 0.3$), ceteris paribus. This comparison is summarized in Table 5-1. As the variance was raised, both the optimal trigger level, H, and the value of investing at the optimal trigger, $\rho V(H)$, increased at an increasing rate. More uncertain returns correspond with higher values of the investment option, due to the value of the option to postpone investing.

Table 5-1: Comparative Results from Changing the Variance of Returns to Investing

Investment Indicator	$\sigma_V^2 = 0.043$	$\sigma^2 =$ 0.0625	$\sigma^2 = 0.09$
Modified hurdle rate (ρ')	6.83 percent	8 percent	9.57 percent
Optimal investment trigger (H)	\$190,063	\$222,529	\$265,878
Annualized value of the investment option at H ($\rho V(H)$)	\$106,614	\$139,080	\$182,430

Note: For all three scenarios, $\rho = 0.03$, Q = \$996,200, and M = \$83,448.

Responsiveness to Changes in Variance

The responsiveness of the optimal trigger to changes in the estimated variance on returns from investing was analyzed using a sensitivity index (Boggess and Amerling, 1983), also known as an interval elasticity. A sensitivity index is an estimate of the relative impact of a change in the variance on the optimal investment trigger. The formula for a sensitivity index is

$$\eta_\sigma = \frac{\ln(H) - \ln(H_V)}{\ln(\sigma^2) - \ln(\sigma_V^2)} . \tag{5-9}$$

A sensitivity index is a pure number. Sensitivity indices facilitate comparisons of the effects of the change in a parameter on a statistic used as a decision criterion. Two sensitivity indices were calculated. The change in variance from $\sigma_V^2 = 0.043$ to $\sigma^2 = 0.0625$ corresponds with a five percent change in the standard deviation on the expected returns from investing; over this interval, the sensitivity index was $\eta_\sigma =$ 0.42. Over this range, a one percent increase in variance raises the optimal investment trigger by 0.42 percent. Raising the variance from $\sigma^2 = 0.0625$ to $\sigma^2 =$ 0.09 generated a sensitivity index of $\eta_\sigma = 0.49$. Over this interval, a one percent increase in the variance increased the optimal investment trigger by 0.49 percent.

In summary, raising the variance on expected returns has the unambiguous effect of making the option to postpone investing more valuable, as reflected by increases in modified hurdle rates (ρ') and by higher optimal investment triggers (H). The null hypothesis was not rejected: increasing the variance on expected returns from investing raised the modified hurdle rate and the optimal investment trigger.

Varying the Discount Rate on Returns from Investing

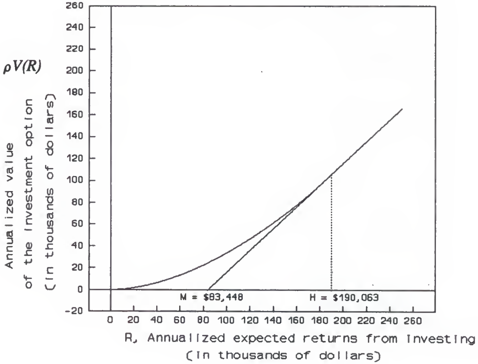
The third hypothesis specified a positive correlation between the discount rate and the modified hurdle rate (ρ'), and an inverse relationship between the discount rate and the optimal investment trigger (*H*) and also between the discount rate and the overall value of the investment option, *V(H)*. That is, raising the discount rate used in the investment analysis was hypothesized to increase ρ' and lower *H* and *V(H)*; lowering the discount rate was hypothesized to lower ρ' and raise *H* and *V(H)*.

In investment analysis, the discount rate is chosen by the investor. As a rule of thumb, higher discount rates are applied to risky projects. Individual risk preferences enter into the selecting the appropriate trade-off between investing today or tomorrow. The discount rate employed in evaluating investment options determines the relative importance associated with current revenues, compared with returns received in future periods. A low discount rate means future returns are relatively more important than current returns, that is, the option to wait to invest is worth more. Assigning a high discount rate puts more weight on current returns than on future returns thus making it worth less to wait.

Sensitivity analysis was conducted to demonstrate the effect of changing the discount rate on the expected returns from investing. Three scenarios were analyzed, ceteris paribus: the baseline case, $\rho_V = 0.03$ was contrasted with $\rho = 0.02$ and $\rho = 0.04$. The variance used in the analysis was $\sigma^2 = 0.043$, and the sunk cost of the investment was held at $Q = \$996,200$.

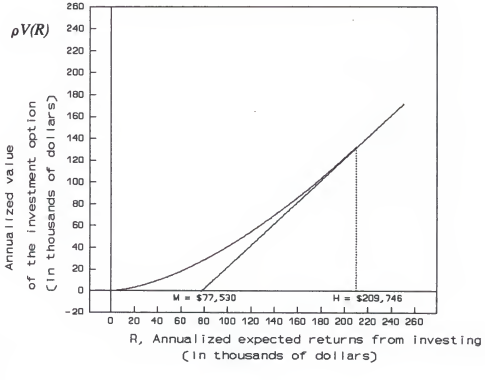
The baseline scenario is presented in Figure 5-2, where $\rho_V = 0.03$ and M = \$83,448 (the value of an annuity to yield Q after 15 years at 3 percent). This graph plots the annualized value of the option to postpone investing, $\rho V(R)$, as an increasing function of expected returns from investing (R). The straight line plots the value of investing, and the curve above it plots the value of the option to wait. At the optimal investment trigger, $\rho V(H)$ = \$106,614.

Figure 5-2: Break-even and Optimal Investment Triggers for the Baseline Scenario (ρ = 0.03)



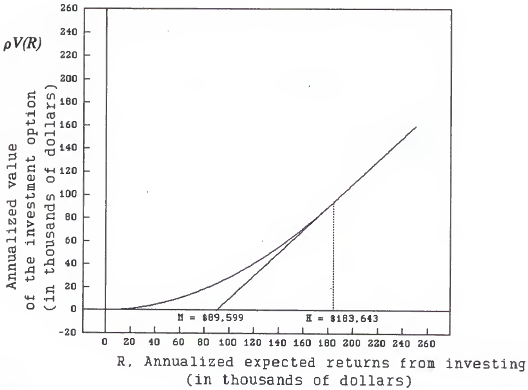
The effect of lowering the discount rate to $\rho = 0.02$ is shown in Figure 5-3, where the annualized value of the opportunity to invest, $\rho V(R)$, is plotted as an increasing function of expected returns from investing (R). Break-even returns from investing (M = \$77,530) are lower than in the baseline scenario. Conversely, lowering the discount rate increased the expected returns from investing required to trigger investment (H = \$209,746). The straight line plots the value of investing, and the curve above it plots the value of the option to wait. At the optimal investment trigger, $\rho V(H)$ = \$132,216. A lower discount raises the value of the option to postpone investing, relative to the baseline scenario.

Figure 5-3: Break-even and Optimal Investment Triggers for a Low Discount Rate ($\rho = 0.02$)



The effect of raising the discount rate to $\rho = 0.04$ is shown in Figure 5-4, where the annualized value of the opportunity to invest, $\rho V(R)$, is plotted as an increasing function of expected returns from investing (R). Break-even returns from investing (M = \$89,599) are higher than in the baseline scenario. Conversely, raising the discount rate lowered the expected returns from investing required to trigger investment (H = \$183,643). The straight line plots the value of investing, and the curve above it plots the value of the option to wait. At the optimal investment trigger, $\rho V(H)$ = \$94,043. A higher discount rate lowers the value of the option to postpone investing relative to the baseline scenario.

<u>Figure 5-4</u>: Break-even and Optimal Investment Triggers for a High Discount Rate ($\rho = 0.04$)



How the Discount Rate Affects Investment Analysis

A discount rate determines the relative value to the investor of current versus future returns. Choosing a higher discount rate implies that future returns (and thus waiting) are worth less, relatively, than when a lower discount rate is chosen. The discount rate determines the weights used in evaluating the trade-off between the opportunity cost of foregone potential returns from investing and the value of postponing an irreversible investment in order to collect more information.

Comparative analysis of the effect of varying the discount rate on the break-even level of expected returns from investing (*M*), the modified hurdle rate (ρ'), the optimal investment trigger (*H*), and the annualized value of the investment option at the optimal trigger, $\rho V(H)$, ceteris paribus, is summarized in Table 5-2.

Table 5-2: Comparative Results from Varying the Discount Rate

Investment Indicator	$\rho = 0.02$	$\rho_V = 0.03$	$\rho = 0.04$
Modified hurdle rate (ρ')[4]	5.42 percent	6.83 percent	8.20 percent
Optimal investment trigger (*H*)	\$209,746	\$190,063	\$183,643
Annualized value of the investment option at *H*, $\rho V(H)$	\$132,216	\$106,614	\$94,043
Break-even expected returns (M)	\$77,530	\$83,448	\$89,599

Note: For all three scenarios, $\sigma^2 = 0.043$ and Q = \$996,200.

[4]The formula for the modified hurdle rate, from Equation (5-2), is

$$\rho' = \frac{\beta}{\beta - 1} \rho ,$$

where β is given in Equation (5-1). For $\rho = 0.02$, β is 1.586. For $\rho = 0.03$, β is 1.783. For $\rho = 0.04$, β is 1.953.

Varying the discount rate has a differetial effects: as the discount rate is lowered, the break-even level of expected returns (M) is lower than the baseline (M_V), yet the optimal investment trigger (H) increases as the discount rate is lowered. Conversely, raising the discount rate increases M relative to M_V, but lowers the optimal investment trigger, such that $H < H_V$.

This differential effect of changing the discount rate has interesting implications. Under a conventional present-value investment analysis, a lower discount rate ranks an investment opportunity as more likely to break even ($M < M_V$); a higher discount rate ranks an investment opportunity as less likely to break even ($M > M_V$). In contrast, an investment analysis which accounts for irreversibility and uncertainty yields the opposite ranking: a lower discount rate raises the optimal investment trigger ($H_V < H$) relative to the baseline scenario, whereas a higher discount rate lowers the optimal investment trigger ($H_V > H$).

Differences in the annualized value of the option to wait to invest, $\rho V(H)$, as determined by the discount rate, account for this reversal in investment rankings. Choosing a lower discount rate weights future returns more heavily than current returns, thus the option to wait to invest is worth more, $\rho V(H) > \rho V(H_V)$ relative to the baseline. If payoffs in the future are more important than current returns, then an investor is less willing to risk future payoffs being low and thus is more willing to pay for the option to postpone. In contrast, selecting a higher discount rate implies that current returns are more important than future returns, so $\rho V(H) < \rho V(H_V)$ because the option to invest is less valuable compared with the baseline.

Responsiveness of Investment to Changes in the Discount Rate

A sensitivity index was calculated to assess the responsiveness of the optimal investment trigger (H) to changes in the discount rate. The calculation used for the sensitivity index was:

$$\eta_\rho = \frac{\ln(H) - \ln(H_V)}{\ln(\rho) - \ln(\rho_V^2)} . \tag{5-10}$$

Two sensitivity indices were compared, to analyze the effect on the optimal investment trigger of changing the discount rate by one percent, from the baseline, $\rho_V = 0.03$. The change in the discount rate from $\rho_V = 0.03$ to $\rho = 0.02$ resulted in a sensitivity index of $\eta_\rho = -0.24$. Over this interval, a unit decrease in the discount rate raised the optimal investment trigger by 0.24 percent. Raising the discount rate from $\rho_V = 0.03$ to $\rho = 0.04$ generated a sensitivity index of $\eta_\rho = -0.12$. The effect of raising the discount rate is less than the effect of lowering the discount rate by the same amount. A one percent increase in the discount rate corresponds with a drop in the optimal investment trigger of 0.12 percent.

Sensitivity indices are pure numbers, which facilitates comparison between the effects of changes in different parameters on investment behavior. The sensitivity indices calculated to assess the effect on the optimal investment trigger of changing the variance were $\eta_\sigma = 0.42$ (for the interval $\sigma_V^2 = 0.043$ to $\sigma^2 = 0.0625$) and $\eta_\sigma = 0.49$ (for the interval $\sigma^2 = 0.0625$ to $\sigma^2 = 0.09$). The responsiveness of the optimal investment trigger to changes in the variance is more than twice as significant as its responsiveness to changes in the discount rate.

In summary, raising the discount rate makes the option to postpone investing less valuable and lowering the discount rate makes it more valuable. The change in the optimal investment trigger is less than proportional to the change in the discount rate because the discount rate affects the opportunity cost of waiting more than it affects the present value of expected future returns.

A Numerical Example

To see that changing the variance has a more pronounced effect on the optimal investment trigger than has level of the discount rate, a numerical example is presented. Note that as $\sigma^2 \rightarrow 0$, then $H \rightarrow M$. This numerical example shows optimal triggers for $\rho = 0.02$ and $\rho = 0.03$ with a baseline variance of $\sigma^2 = 0.043$. Changing the variance to $\sigma^2 = 0.034376$ where $\rho = 0.02$ results in an optimal trigger of $H = \$190{,}063$ which is exactly equal to the optimal trigger where $\sigma^2 = 0.043$ and $\rho = 0.03$ (Table 5.3).

Table 5.3: A Numerical Example

	BASELINE	BASELINE	CHANGED VARIANCE
Variance	$\sigma^2 = 0.043$	$\sigma^2 = 0.043$	$\sigma^2 = 0.034376$
Discount Rate	$\rho = 0.03$	$\rho = 0.02$	$\rho = 0.02$
Optimal Trigger	$H = \$190{,}063$	$H = \$209{,}746$	$H = \$190{,}063$

Uncertain Invesment Costs

The fourth hypothesis specified that increasing the variance on the expected cost of initiating an investment increases the level of the optimal investment trigger. To test the effect of uncertain investment costs, the cost of investing was modeled as a random variable.

In the baseline scenario, the cost of installing a free stall facility was fixed. Whether the investment was made now or later, the cost of investing was the same. To reflect uncertain investment costs, the sunk cost of the investment, K, is partitioned into a time-invariant component (Q) and a random component (I), such that

$$K = Q + I \,, \tag{5-11}$$

as stated in Equation (4-13). For the baseline scenario, $E(I) = I$. Evolving compliance requirements or changes in other construction factors may affect the cost of investing, such that $I \neq E(I)$.

The fourth hypothesis test involved modeling the cost of investing with a random component, following the process described in Equation (4-15). The uncertain cost component, ε_I, was specified to be a normally-distributed random variate with $\mu_\varepsilon = 0$ and $\sigma_\varepsilon = \$95{,}000$; the quantity ε_I was subtracted from the total discounted returns from investing, (Z). The standard deviation used in this hypothesis test was ten percent of the total estimated cost of installing a free stall facility. This zero-mean specification models the cost of investing as having an equal probability of being either higher or lower than expected.

Positive values of ε_I subtracted from the total discounted returns from investing correspond with the behavioral hypothesis that the cost of satisfying environmental regulations or other construction costs will be higher than expected, adding to the cost of investing in new dairy facilities. Negative values of ε_I are in accord with the opposite viewpoint, the notion that the cost of investing might be less than expected.

Some central Texas producers expect ε_I to be positive because the nominal cost of environmental compliance in Texas doubled between 1987 and 1992, with annual increases between 15 and 20 percent (Pagano et al., 1993b). The 1992 permitting costs on a new facility in central Texas were over $100,000 (Stalcup, 1992). Others are optimistic that more reasonable environmental policies are inevitable: one central Texas producer noted that since manure is not a toxic substance, it is likely that the public and regulators will soon recognize the high opportunity cost of regulating dairies (Pagano et al., 1993b). Modeling the zero-mean random variable recognized both behavioral hypotheses as possibilities.

Following procedures detailed in Chapter 4, the trend and the variance on the expected returns from investing were estimated based on 100 Monte Carlo simulations. The estimated value of the trend was μ_Z = -0.00169 and the estimated variance of expected returns from investing was σ_Z^2 = 0.048 (Appendix B). A student's t-test was conducted to verify that $\mu_Z \approx 0$. Formally,

$$\begin{aligned} H_0&: \ \mu_Z = 0 \\ H_A&: \ \mu_Z \neq 0 \ . \end{aligned} \tag{5-12}$$

The standard deviation of μ_Z from 100 estimates of the trend was $\sigma_\mu = 0.001365$ and the t-test statistic was -1.2381 (Appendix B). Based on a two-tailed t-test, the null hypothesis is not rejected.

For the free stall investment project, recall that for the baseline scenario where investment costs were fixed, β/β-1 was 2.28 and ρ' was 6.83 percent. Adding in uncertain investment costs increased the variance of expected returns from 0.043 to 0.048 resulting in an increase in the multiplier to β_Z/β_Z-1 = 2.4. The modified trigger rate, ρ_Z', was 7.22 percent.

A likelihood ratio test was conducted to test whether uncertainty about the cost of investing had a statistically significant effect on the modified hurdle rate.[5]

$$\begin{aligned} H_0&: \rho_V' = \rho_Z' \\ H_A&: \rho_V' \neq \rho_Z' \end{aligned} \tag{5-13}$$

The standard deviation of ρ_Z', calculated from 100 simulation estimates of ρ_Z' was 0.001944 and the likelihood test statistic was 140.52 (Appendix B). In accord with the null hypothesis, the likelihood ratio is assumed to be distributed as a chi-square variate with one degree of freedom. The null hypothesis was rejected and the alternative hypothesis was supported.

When a producer considers an investment in dairy housing modifications, the costs are not all known with certainty before the project begins. Several factors can

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[5]In the construction of the test, it is assumed that ρ_V' and ρ_Z' are normally distributed. This test took into account differences in the standard deviations for the two distributions.

affect the final cost of modifying an existing open lot facility into a free stall dairy. Costs of materials may increase during the construction period. The engineering requirements on a new facility may go up or down, due to changes in environmental permitting requirements. Building costs may also go down, due to improvements in construction processes or innovations in waste management systems required for environmental compliance. Increased competition can spur lower costs, in response to growth in demand either for dairy housing improvements or for environmental compliance-oriented technologies.

In summary, the effect of uncertainty about the costs of investing made a difference in investment behavior. Investment cost uncertainty increased the optimal investment trigger, from H_V = \$190,063 to H_Z = \$198,606.

Further Probing Uncertain Future Investment Costs

The fifth hypothesis was that it makes a difference in investment behavior whether future costs of investing are expected to increase or decrease.

Higher Expected Future Investment Costs

One plausible scenario is for dairy producers to expect the future costs of investing to be higher than the cost of investing today, due to escalating compliance-related costs. The investment cost today is observable ($Q = K$ and $I = 0$) but waiting until next period to invest means $Q = K + I$ where ε_I is positive. Higher sunk costs are deducted from the aggregate returns from investing (Z). The net effect

is that the expected level of Z is lower in future periods than if the investment were initiated in the current period. This corresponds with a negative trend, $-\mu_Z$. The larger the expected increase in future investment costs, the larger the negative trend.

Handling a non-zero trend, μ_Z, in expected returns from investing required a slight adjustment to the formula for the modified hurdle rate. According to Dixit,

> when $\mu \neq 0$ the future revenue stream is expected to grow at the rate μ, and is discounted back at rate ρ, so its expected value is $R/(\rho - \mu)$. The net worth of investing is $R/(\rho - \mu) - K$. The Marshallian trigger is $M = (\rho - \mu)K$. Otherwise, the calculation proceeds . . . [as outlined in the "Theory" chapter], and the optimal trigger H is still $\beta/(\beta - 1)M$. Therefore, the adjusted discount rate ρ^* is defined by
>
> $$\rho^* = \rho' - \mu = \frac{\beta}{\beta - 1}(\rho - \mu) \qquad (5\text{-}14)$$

(1992b, p. 130).

In calculating the modified hurdle rate, a negative trend has a multiplied effect. Following Equation (5-14), the calculation involves two steps: first the initial hurdle rate is adjusted to account for the trend, such that $\rho_Z' = \rho - \mu_Z$. Where μ_Z is negative, then $\rho_Z' > \rho$. Current returns are relatively more important than without taking into account $-\mu_Z$. The second step involves the multiplier β_Z/β_Z-1, where $\rho_Z^* = \beta_Z/\beta_Z-1\ \rho_Z'$. The unambiguous result is a marked increase in the modified hurdle rate, ρ_Z^*.

For the potential investor, the choice is between investing today when investment costs are observable, versus postponing investment in light of the expectation that the cost of investing will increase. The decision criteria from this investment analysis are ρ_V' versus ρ_Z^*, respectively. Since ρ_V' is lower than ρ_Z^*, if

the cost of investing is expected to go up, then it is best to invest now or not at all. Optimal investment behavior is initiating the investment if the expected rate of return is ρ_V' or above. Otherwise, if future investment costs continue to rise, following the producers' expectations, then the investment opportunity is ignored. Only if the investor is surprised--if the cost of investing falls or returns from investing are higher than expected--does she re-evaluate the option to invest.

Lower Expected Future Investment Costs

Another possible behavioral hypothesis is the expectation that future investment costs are likely to be lower than the cost of investing today, due to technological innovation or due to greater flexibility in pollution abatement options on new facilities from regulatory agencies in the future. This is modeled with the investment cost today as observable ($Q = K$ and $I = 0$) but in the next period the cost of investing is lower than today, with $Q = K + I$ and ε_I being negative. If the investment were postponed, a lower sunk cost of investing would translate into an increase in the expected aggregate returns from investing (Z). The likelihood that initiating the investment will cost less in the future than now results in a positive trend, μ_Z, in Z. The greater the expected savings, the larger the positive trend.

The positive trend has a multiplied effect on the modified hurdle rate. Following Equation (5-14), the positive trend is first subtracted from the discount rate used in the analysis, $\rho_Z' = \rho - \mu_Z$. Since μ_Z is positive, $\rho_Z' < \rho$. Future returns from investing are relatively more important than were future returns as analyzed in

the baseline scenario. The second step in calculating the modified hurdle rate involves the multiplier β_Z/β_Z-1, where $\rho_Z^* = \beta_Z/\beta_Z$-1 ρ_Z'. The multiplied change associated with this adjustment is less than in the baseline scenario where $\mu = 0$. Unless β/β-1 is very large (due to σ^2 being very large), the expected effect from a positive trend is that ρ_Z^* is less than ρ. The required rate of return from investing necessary to signal investment is lower when ρ_Z^* is the criterion than the return required to be greater than ρ.

For a dairy producer considering the free stall investment project, the decision is between investing today versus waiting in order to take advantage of expected investment cost savings. The modified hurdle rates from this investment analysis, respectively ρ and ρ_Z^* for the two options, indicate that the value of postponing outweighs the cost of foregone revenues, as $\rho_Z^* < \rho$. Waiting is advisable. This effect holds unless the change in the variance on expected returns to investing due to ε_I is significant, swamping the effect of the positive trend.

Variance Increases due to an Additional Stochastic Factor

Generally speaking, an additional random variable, ε_I, in the simulation model (when $Q = K + I$, $E(I) = \varepsilon_I$ and $\varepsilon_I \neq 0$) has the effect of raising the variance on expected returns to investing. This effect was demonstrated in the sensitivity analysis to test the fourth hypothesis, where modeling to include an uncertain cost component, ε_I--a normally-distributed variable with zero mean and a standard deviation of \$95,000--raised the variance on expected returns to investing by approximately five

percent. Regardless of whether future costs of investing are expected to rise or fall, an additional stochastic variable in the model is expected to raise the variance, ceteris paribus. The magnitude of the increase in variance depends on the size of ε_I and on its distribution.

In summary, if evolving environmental compliance regulations or other uncertainties generate expectations among dairy producers that the future cost of investing is likely to be higher, then it is optimal investment behavior to disregard the option to postpone investment. Unless the modified hurdle rate based on observable investment costs is acceptable, the investor will rule out the investment. On the other hand, the behavioral hypothesis that the future cost of investing may be lower than the cost today leads to optimal investment criteria which weight more heavily the value of waiting and watching. The expectation that the cost of investing will fall makes the option worth watching. At some point the opportunity cost of foregone benefits from investing will be larger than the value of waiting. This opportunity cost gets higher as time passes, thus there are grounds for optimism that it will be optimal to invest sometime rather never.

In the final chapter, "Policy Implications and Conclusions," the importance of these results for policy design and implementation are discussed, opportunities for further research are proposed, and conclusions are drawn.

CHAPTER 6
POLICY IMPLICATIONS AND CONCLUSIONS

The general implication of this research is that uncertainty and irreversibility make a difference in optimal investment behavior. These empirical results show that the hurdle rate applied as an investment criterion more than doubles when modified to account for the effect of irreversibility and uncertainty on optimal investment timing. When investors are uncertain about the costs of investing, the modified hurdle rate is further increased. Dissonance concerning future policies may have the unintentional consequence of discouraging desirable technology adoption.

Carol Browner, administrator of the U.S. Environmental Protection Agency (EPA), in her confirmation hearing before the Senate, acknowledged that unclear policy signals may have unwanted effects on investment behavior. She called for

> a new era in communication between the EPA and America's business community. . . . The adversarial relationship which now exists **ignores the real complexities** of environmental and business problems; creates **damaging delays** in the regulatory process; and often **unnecessarily harms business** without significantly aiding the environment. . . .
> EPA must deliver quick, consistent decisions (1993).
> [emphasis added]

This statement indicates a general awareness among environmental policy makers of the unnecessary inefficiencies associated with uncertainty due to ambiguities about permitting requirements and procedures. It may be a teachable moment.

The purpose of this chapter is to present a synopsis of the major research findings, to summarize the implications of these research results for policy design and implementation, and to suggest opportunities for further research.

Synopsis of Major Findings

The empirical results presented in the previous chapter document the effect of uncertainty and irreversibility on dairy producers' propensity to adopt free stall technology. Installing free stall facilities on an existing large dairy requires a large outlay of capital (approximately $950,000 for a 1000-cow facility). Modifying housing on a dairy is an inherently risky investment. Accounting for the effects of uncertainty about feed costs and uncertainty about milk production from installing free stall facilities more than doubled the expected rate of return from investing required to trigger the decision to invest (the hurdle rate). Sensitivity analysis showed that modeling the cost of investing as uncertain further exacerbated the effects of irreversibility and uncertainty on investment behavior. The more uncertain are investment costs, the more likely that the investment will be postponed or ruled out.

Review of Key Results

To decide whether and when to make an investment, the first step in economic analysis is capital budgeting to forecast the expected net returns from investing, $E(R)$. The conventional investment criterion says to proceed with a project if the present value of expected returns are equal to or greater than the capital costs associated with

installing it. The Marshallian trigger (*M*) is the level where the project is expected to break even, that is, where the net present value of the investment equals zero. The maintained assumption implicit in this Marshallian criterion is that the decision is either to invest or not to invest. The option to delay investment is not considered.

The modified investment trigger. Uncertainty about expected returns from investing was considered in valuing the option to postpone an irreversible investment. The modified investment trigger (*H*) reflects the value of investing now (which is *M*) plus the value of the option to postpone investing. The exact adjustment is $\rho V(R)$, the annualized value of the option to wait to invest; that is, $M + \rho V(R) = H$.

Empirical estimates of the modified investment trigger. Empirical results of the analysis of the decision whether and when to invest in a free stall dairy facility lead to a Marshallian trigger of $M = \$83{,}448$. The modified investment trigger, accounting for irreversibility and uncertainty, was 2.28 times greater than M, or $H_V = \$190{,}063$. An adjustment to depict uncertainty about the cost of investing further increased the modified investment hurdle to $H_Z = \$198{,}606$, a level of expected returns from investing 2.4 times higher than the Marshallian level.

Modeling risk preferences as exogenous. The modified investment trigger, *H*, reflects the value of the option to postpone an uncertain and irreversible investment. This modification to the optimal investment trigger is independent of the investor's risk preferences. There is a maintained assumption of risk neutrality in the adjustments which account for irreversibility and uncertainty (that is, *M* being modified as *H* and ρ being modified as ρ'). What accounts for the difference between

M and *H* or between ρ and ρ' is the expected gains from the option to postpone investing, in order to assimilate additional information about expected returns from the investment. To account for risk preferences, sensitivity analysis can be conducted to assess the effect of varying the discount rates applied in the investment analysis.

The effect of varying the discount rate. Sensitivity analysis indicated that changing the discount rate had differential effects on *M* and *H*: lowering the discount rate lowered *M* but raised *H*, and raising the discount rate increased *M* but lowered *H*. This differential effect has interesting implications. A higher discount rate (use of a more risk-averse investment criterion) is associated with the likelihood of a delay in optimal investment; using a Marshallian decision criterion, this means *M* is above its baseline level. On the other hand, a higher discount rate had an opposite effect on the modified trigger: it deflated the value of the option to postpone investing sufficiently that the decrease exceeded the increase in the Marshallian trigger and thus the modified investment trigger declined. The converse was confirmed by empirical results regarding the effect of lowering the discount rate.

The effect of changing the variance. Results of sensitivity analysis were unambiguous: as variability in expected returns from investing increases, the level of expected returns required to trigger optimal investment also increases. Changing variance had a greater effect on the optimal investment trigger than raising or lowering the discount rate. A comparison of sensitivity indices indicated that changing the variance has approximately double the effect on the optimal investment trigger compared with the effect of changing the discount rate.

Modeling investment costs as uncertain. The baseline analysis accounted for uncertainty in expected returns from investing in a free stall facility due to uncertainty about feed costs and uncertainty about increases in milk production due to improved cow comfort. A maintained assumption built into the baseline scenario was that the cost of investing was known with certainty: whether the free stall facility was built now or in the future, in the baseline analysis the cost of the investment was fixed.

A revised scenario was modeled, to account for uncertainty about the cost of investing. Investment cost uncertainty was depicted by specifying the cost of the current investment as including a random component which raised or lowered the investment cost by ten percent. The probability of investment costs being higher or lower than expected was equal in this specification; the random component was a normal variate with a zero mean and a standard deviation of \$95,000 (ten percent of the expected cost of the facility). This simple adjustment raised the modified investment trigger from H_V = \$190,063 to H_Z = \$198,606.

Insights from *Ex Ante* Forecasting

This empirical research was the first application in agriculture of a conceptual framework for modeling the effects of irreversibility and uncertainty on investment behavior. This approach suggests an alternative to existing techniques for analyzing the adoption and diffusion of new technologies: it demonstrates a method for modeling the phenomenon *ex ante*, whereas conventional analysis has focused on *ex post* assessment of producers' responsiveness to new technologies.

Empirical results describing the decision whether and when to adopt a free stall dairy facility support the theoretical proposition that accounting for the value of the option to postpone investing makes a difference in the optimal timing of risky investments, particularly under irreversibility (where sunk costs are large or mistaken investments are otherwise costly). These empirical findings are consistent with results from other empirical applications of analysis of investment under irreversibility and uncertainty, as overviewed by Pindyck (1991b) and Dixit (1992b). They also lend credence to Dixit's notion that perhaps "economists should alter our orthodox views on investment and rewrite our textbooks" (1992b, p. 116) to include a conceptual framework which accounts for irreversibility and uncertainty.

The innovation offered by this application of the conceptual framework for analysis of investment under irreversibility and uncertainty was the use of simulation modeling to generate *ex ante* forecasts of optimal investment behavior under a particular set of risky conditions.[1] Results from *ex ante* forecasting may offer useful information for designing and implementing policies geared toward promoting the adoption of new technologies. Conventional analysis of adoption is conducted using time-series data, thus is necessarily an *ex post* analysis. A drawback of an *ex post* perspective is that constraints to adoption may be identified too late to modify policy instruments, and too late for these modifications to be translated into policy changes which might lead to accelerated adoption. Accordingly, policy goals may go unmet.

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[1]The simulation modeling was based on a detailed profile of expectations about uncertain returns from investing and uncertainty concerning the cost of investing.

Ex ante forecasting of likely investments in a new technology may offer information to aid in finetuning policies geared toward promoting adoption. Given a profile of potential adopters' perceptions of the expected returns from investing in a new technology--including the uncertain parameters--it is possible to profile whether the technology's perceived cost-effectiveness is likely to make adoption desirable in the current period for a risk-neutral investor. Any troublesome uncertainties or constraints can be pinpointed, and their likely effects on investment behavior can be quantified. Sensitivity analysis can be conducted to determine how risk preferences are likely to affect adoption behavior.

Policy Implications

The power in *ex ante* forecasting is in its potential to generate information required to design appropriate and effective policy instruments. Alternatively, if the policy is in the process of being implemented, *ex ante* forecasting offers the information needed to modify policy instruments, in order to make policy outcomes more consistent with policy objectives.

A Conceptual Framework for Policy Analysis

For thinking about how best to use information from *ex ante* forecasting to inform the design and implementation of policy, concepts from signal detection theory (Green, 1992; Green and Swets, 1964) are proposed as guidelines.

Clarifying the signal. Decisive policy steps--a clear articulation of the environmental compliance requirements for dairy waste management--would eliminate one source of uncertainty which affects technology adoption decision making. Grandfathering free stall technology into state or federal regulations as the best available technology and issuing permits assuring dairy producers that this investment would guarantee their compliance for some fixed period would send a positive signal in favor of investment.

Reducing the noise. Dissonance concerning future costs of compliance creates a disincentive to investment in irreversible technologies. In Texas, for example, in July, 1992, the EPA Region VI introduced requirements for a general National Pollution Discharge Elimination Permit (NPDES) for all large dairies ("National...", 1992), but the regulation was not finalized until February, 1993 ("National...", 1993) and implementation of new permitting procedures was scheduled to begin after May, 1993. As of mid-July, 1993, discussions about record-keeping required under the new NPDES general permit--specifically, how to file a pollution prevention plan for a permitted dairy--were still underway, still not finalized (Brister, 1993b). Amid speculation about what this permit would require and how it might be enforced, many Texas dairy producers have postponed investment decisions during 1992 and 1993. The value of waiting was magnified by indeterminacies about policy content and intent. Minimizing the duration of uncertainty about evolving compliance requirements--reducing the noise masking policy signals--is an important strategy for improving the effectiveness of policies aimed to promote technology adoption.

Improving detector performance. A third approach to increase dairy producers' responsiveness to technology investment opportunities, like free stall housing, is to increase human capital. Education and technical assistance programming are likely to improve producers' understanding of environmental compliance requirements and their sophistication at judging the potential for both production-enhancing and pollution-abatement benefits from the same technology and, more importantly, whether they could make it work. Management is the key to successful adoption of free stall dairy technology.

Specific Policy Prescriptions

Ex ante forecasting may offer specific suggestions for modifying policy design and implementation in order to relax constraints blocking the adoption of free stall dairy technology.

Clarifying the signal. An empirical profile of Texas dairy producers' perceptions of the expected returns from adopting a new technology identified a discrepancy between the optimal investment trigger and the perceived level of expected returns to investing. This gap may be due to misinformation or misconceptions about the technology's performance and the environmental compliance aspects of its performance.[2] If misinformation or misconceptions can be cleared up

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[2]For example, scientific research may someday establish and quantify the potential for reductions in the long-run cost of environmental compliance due to the pollution-abatement benefits of free stall dairying. Such information is not currently available, thus current compliance costs are not viewed as significantly different for free stall dairying, compared with the costs of compliance on an open lot dairy.

through educational programming and technical assistance, then free stall adoption rates are likely to increase.

Reducing the noise. As in this case, where there is a difference between the optimal investment trigger and the actual expected returns from investing in free stall technology, then it is policy-relevant to know, *ex ante*, that producers are unlikely to adopt it. If adoption of the technology has aspects of a public good--for example, it being a production-enhancing technology which also has pollution-abatement attributes, such as free stall dairy housing--then it might be worth offering cost-sharing to those willing to adopt the technology. Cost-sharing would serve as compensation to dairy producers willing to take on the financial risk associated with adopting a technology which might have socially-desirable environmental benefits (reducing the risk of water quality damages or odor from dairying) in addition to its production benefits. Ceteris paribus, these production-enhancing benefits, by themselves, are likely to be insufficient to justify adoption of free stalls.

The premium required to promote adoption is the difference between $E(R)$ and H. Calculating this premium may help in determining whether offering cost-sharing to encourage adoption of the technology by a target group of adopters (those to whom cost-sharing would be available) is consistent with policy priorities.

Improving detector performance. If the optimal investment trigger were in the neighborhood of what potential adopters believe to be the expected returns from investing in free stall facilities, then adoption would be likely to happen without further policy intervention. As long as producers are all aware of the availability and

cost-effectiveness of a new technology, devoting resources to its promotion may be unnecessary (or may have high opportunity costs). Accordingly, a constructive policy response--toward supporting successful adoption--may be to commit resources to information campaigns and technical support services, in order to assure that producers who invest are then able to manage the technology in order to meet its optimal performance targets.

Policy Dialogue Opportunities

Positive auxiliary benefits to the policy process from empirical research activities merit acknowledgment. Conducting research to generate *ex ante* forecasts of producers' responsiveness to a new technology requires grassroots data collection. An essential requirement for an accurate forecast of potential adopters' likely investment behavior is a profile of their perceptions of the performance of a new technology--including confidence intervals for estimates on key parameters--and of the expected returns from investing. The act of collecting such data requires in-depth discussions with producers and feedback from those responsible for policy implementation. Participation in this process helps producers to realize that those designing policies are concerned about the cost effectiveness and the economic feasibility of the technologies being recommended or required for environmental compliance.

Producers are responsive to the opportunity to supply information about an actual technology option being considered, both its positive and negative aspects.

They appreciate the chance to make their views heard concerning the complex choices associated with juggling farm management objectives and environmental compliance obligations. Dialogue is most constructive when it focuses on a particular technology and on its costs and returns. Talking about real numbers and actual policy alternatives tends to downplay the emotions often associated with discussions of environmental regulations which may impinge upon agricultural property rights. Data collection to support economic analysis of policy options is an opportunity to build rapport between producers and those who design and implement environmental policy, an improvement compared with adversarial relationships which can otherwise evolve. Dialogue focused on real options diffuses heat and sheds light.

Further Research Opportunities

Two extensions to this research are proposed, toward improving its usefulness for policy analysis.

More Precise Modeling of Uncertain Investment Costs

The research findings involved the use of a geometric Brownian motion process to model the time path of stochastic variables. Implicit in the Ito process, which is the basis for this specification, is an assumption that the time path of the stochastic variable follows a random walk. Geometric growth is built into the variance. While this assumption may be appropriate for modeling uncertainty about some parameters, such as price, it may over-dramatize the compounded effect of

uncertainty about evolving compliance requirements on investment behavior. An opportunity for further development of this empirical research is experimentation with alternative stochastic processes, in particular a Poisson specification, as discussed by Cox and Ross (1976).

Modeling Aggregate Behavior

These research results profile the likely investment behavior of Texas dairy producers in response to the opportunity to adopt free stall technology. For policy purposes, one disadvantage of this case study approach is its situation-specificity. It may be difficult to generalize the implications of these research findings, in order to glean insights which apply to the adoption behavior of another group of producers in another region, or to a different technology adoption opportunity.

These research findings offer abundant evidence, however, that investment behavior is a complex phenomenon. A solid understanding of what motivates individual behavior is essential to accurate forecasting of responsiveness to new technologies by groups of producers (according to region or according to farm category). The next frontier is to use these micro-foundations to model behavior at the aggregate level. Griliches (1957) projected adoption rates and fitted diffusion curves using econometric techniques. Estimates of adoption rates and diffusion curves have a role to play in both federal- and state-level policy design and implementation. Toward developing such estimates, a priority area of future research is to develop a conceptual framework for econometric forecasting of adoption based

on data generated from simulation models and from profiles of producers' perceptions about new technologies.

Conclusions

Environmental compliance requirements are playing a decisive role in investment decision making in the dairy industry, as well as in other agricultural industries. To the extent that there are technologies with both pollution-abatement and productivity-enhancing attributes, their adoption can both improve the economic viability of agricultural activities and reduce pollution. Promoting environmental quality is an increasingly high societal priority, yet to balance this priority with the task of also maintaining productivity in agriculture is challenging. This paradigm for *ex ante* forecasting of likely investment behavior is proposed as a tool for finetuning policy design and implementation, in the interest of enhancing policy efficiency and effectiveness.

In conclusion, to borrow an idea from Tom Frost, the president of the Frost Bank of Texas: in the land of the blind, the one-eyed man is king.

APPENDIX A
SIMULATION RESULTS: ESTIMATION OF μ_V AND σ_V^2

SEED	μ_V	σ_V^2	β	ρ_V'	$\rho_V' - \rho$	σ_V
1	0.000850	0.046295	1.743397	0.070355	0.040355	0.215163
2	0.001569	0.045303	1.754757	0.069748	0.039748	0.212845
3	0.000256	0.039360	1.832062	0.066055	0.036055	0.198394
4	0.002356	0.046371	1.742543	0.070402	0.040402	0.215339
5	0.000850	0.046295	1.743397	0.070355	0.040355	0.215163
6	0.002451	0.041442	1.802999	0.067360	0.037360	0.203573
7	-0.000596	0.041734	1.799106	0.067542	0.037542	0.204289
8	-0.000521	0.039447	1.830800	0.066110	0.036110	0.198613
9	-0.000445	0.044446	1.764892	0.069221	0.039221	0.210822
10	-0.001868	0.041139	1.807085	0.067171	0.037171	0.202828
11	0.001679	0.042658	1.787065	0.068116	0.038116	0.206538
12	0.000913	0.044848	1.760100	0.069468	0.039468	0.211773
13	0.000045	0.041468	1.802651	0.067376	0.037376	0.203637
14	0.000771	0.045570	1.751661	0.069912	0.039912	0.213471
15	-0.002443	0.044911	1.759355	0.069507	0.039507	0.211922
16	-0.000305	0.044929	1.759143	0.069518	0.039518	0.211965
17	0.000776	0.040719	1.812827	0.066908	0.036908	0.201789
18	0.000134	0.041373	1.803925	0.067317	0.037317	0.203404
19	-0.002448	0.049989	1.704269	0.072597	0.042597	0.223582
20	0.000153	0.041187	1.806434	0.067201	0.037201	0.202946
21	-0.000728	0.039336	1.832411	0.066040	0.036040	0.198333
22	-0.001601	0.046285	1.743510	0.070349	0.040349	0.215139
23	0.002660	0.040149	1.820770	0.066551	0.036551	0.200372
24	-0.001059	0.042268	1.792097	0.067874	0.037874	0.205592
25	0.000423	0.043195	1.780254	0.068449	0.038449	0.207834
26	0.001216	0.048537	1.719086	0.071720	0.041720	0.220311
27	-0.001375	0.042006	1.795518	0.067711	0.037711	0.204954
28	-0.002892	0.040296	1.818704	0.066643	0.036643	0.200739
29	-0.002001	0.043086	1.781625	0.068382	0.038382	0.207572
30	-0.000015	0.040597	1.814512	0.066832	0.036832	0.201487
31	0.001060	0.040702	1.813061	0.066898	0.036898	0.201747
32	0.003014	0.040287	1.818831	0.066638	0.036638	0.200716
33	-0.000531	0.044468	1.764628	0.069235	0.039235	0.210874
34	0.000029	0.046244	1.743972	0.070324	0.040324	0.215044
35	0.000237	0.041991	1.795715	0.067702	0.037702	0.204917
36	0.000036	0.041863	1.797400	0.067622	0.037622	0.204604
37	-0.000520	0.044842	1.760171	0.069465	0.039465	0.211759
38	-0.001360	0.042471	1.789468	0.068000	0.038000	0.206085
39	-0.000541	0.044062	1.769534	0.068985	0.038985	0.209910
40	-0.000728	0.042522	1.788811	0.068032	0.038032	0.206209

SEED	μ_V	σ_V^2	β	ρ_V'	$\rho_V' - \rho$	σ_V
41	0.003422	0.052137	1.683560	0.073888	0.043888	0.228335
42	0.001101	0.045246	1.755422	0.069713	0.039713	0.212711
43	0.000724	0.043047	1.782118	0.068357	0.038357	0.207478
44	-0.000479	0.043310	1.778812	0.068520	0.038520	0.208111
45	0.000661	0.044655	1.762392	0.069350	0.039350	0.211317
46	0.000849	0.039774	1.826093	0.066316	0.036316	0.199434
47	0.002624	0.044498	1.764269	0.069253	0.039253	0.210945
48	0.002186	0.041019	1.808716	0.067096	0.037096	0.202531
49	-0.000919	0.036192	1.881240	0.064043	0.034043	0.190242
50	0.000376	0.045968	1.747099	0.070155	0.040155	0.214401
51	-0.001692	0.043451	1.777054	0.068607	0.038607	0.208449
52	0.002122	0.042735	1.786080	0.068164	0.038164	0.206724
53	-0.000903	0.040903	1.810300	0.067023	0.037023	0.202245
54	0.001589	0.043067	1.781865	0.068370	0.038370	0.207526
55	-0.000542	0.044001	1.770278	0.068947	0.038947	0.209764
56	-0.000552	0.041128	1.807234	0.067164	0.037164	0.202800
57	-0.000851	0.041614	1.800701	0.067467	0.037467	0.203995
58	0.000444	0.044849	1.760088	0.069469	0.039469	0.211776
59	0.001402	0.049114	1.713115	0.072069	0.042069	0.221617
60	0.000852	0.040927	1.809971	0.067038	0.037038	0.202304
61	-0.001545	0.045083	1.757330	0.069613	0.039613	0.212328
62	0.000008	0.044904	1.759438	0.069503	0.039503	0.211906
63	-0.001578	0.046076	1.745872	0.070221	0.040221	0.214653
64	-0.000111	0.046872	1.736963	0.070708	0.040708	0.216500
65	-0.001111	0.043231	1.779800	0.068471	0.038471	0.207921
66	0.000625	0.042425	1.790062	0.067972	0.037972	0.205973
67	0.001967	0.044633	1.762655	0.069336	0.039336	0.211265
68	0.002038	0.041195	1.806333	0.067205	0.037205	0.202964
69	0.000520	0.042596	1.787860	0.068078	0.038078	0.206388
70	-0.000501	0.044076	1.769364	0.068993	0.038993	0.209943
71	0.001099	0.041784	1.798444	0.067573	0.037573	0.204411
72	0.002624	0.038867	1.839301	0.065744	0.035744	0.197147
73	-0.001950	0.044775	1.760965	0.069424	0.039424	0.211601
74	-0.002366	0.043458	1.776966	0.068612	0.038612	0.208466
75	0.000543	0.041545	1.801621	0.067424	0.037424	0.203826
76	-0.000510	0.039773	1.826107	0.066315	0.036315	0.199432
77	0.001556	0.045957	1.747224	0.070149	0.040149	0.214376
78	0.000754	0.040697	1.813130	0.066894	0.036894	0.201735
79	0.000812	0.041680	1.799823	0.067508	0.037508	0.204157
80	-0.000344	0.049273	1.711489	0.072165	0.042165	0.221975
81	0.000122	0.041637	1.800395	0.067482	0.037482	0.204051
82	0.000604	0.044124	1.768781	0.069023	0.039023	0.210057
83	0.001271	0.040038	1.822337	0.066481	0.036481	0.200095
84	0.001268	0.042489	1.789236	0.068011	0.038011	0.206129
85	-0.000057	0.047358	1.731643	0.071004	0.041004	0.217619
86	-0.001169	0.041282	1.805151	0.067260	0.037260	0.203180
87	0.001706	0.042203	1.792942	0.067834	0.037834	0.205434
88	0.000388	0.044107	1.768987	0.069012	0.039012	0.210017
89	0.000320	0.043916	1.771316	0.068895	0.038895	0.209561
90	-0.000298	0.047641	1.728584	0.071176	0.041176	0.218268

SEED	μ_V	σ_V^2	β	ρ_V'	$\rho_V' - \rho$	σ_V
91	-0.000130	0.043950	1.770905	0.068915	0.038915	0.209642
92	0.000766	0.044184	1.768053	0.069060	0.039060	0.210200
93	0.000979	0.037792	1.855595	0.065063	0.035063	0.194402
94	-0.000508	0.043050	1.782080	0.068359	0.038359	0.207485
95	-0.000744	0.042735	1.786080	0.068164	0.038164	0.206724
96	0.000899	0.046392	1.742307	0.070415	0.040415	0.215388
97	0.000733	0.037580	1.858894	0.064929	0.034929	0.193856
98	0.001366	0.042176	1.793294	0.067817	0.037817	0.205368
99	-0.000227	0.040334	1.818172	0.066667	0.036667	0.200833
100	0.001497	0.041152	1.806908	0.067179	0.037179	0.202860
Average	0.000234	0.043154	1.780773	0.068423	0.038423	0.207735
Standard Deviation	0.001294		0.034100	0.001693	0.001693	

Calculation of a t-test statistic for Equation (5-3)

$$H_0: \ \rho = \rho'$$
$$H_A: \ \rho < \rho'$$

The t-test statistic is calculated as

$$\frac{\overline{\rho'} - \rho}{\sigma_{\rho'}} = \frac{0.068423 - 0.03}{0.001693} = 22.69$$

Calculation of a t-test statistic for Equation (5-4)

$$H_0: \ \mu_V = 0$$
$$H_A: \ \mu_V \neq 0$$

The t-test statistic is calculated as

$$\frac{\overline{\mu_V} - \mu}{\sigma_{\mu_V}} = \frac{0.000234 - 0}{0.001294} = 0.1806 \ .$$

SIMULATION RESULTS: ESTIMATION OF μ_Z AND σ_Z^2

APPENDIX B

SEED	μ_Z	σ_Z^2	β	ρ_Z'	$\rho_Z' - \rho$	σ_Z
1	-0.001146	0.05085	1.695801	0.073116	0.043116	0.225499
2	-0.000988	0.05114	1.693000	0.073290	0.043290	0.226142
3	-0.001041	0.052811	1.677339	0.074291	0.044291	0.229806
4	-0.003195	0.045703	1.750130	0.069993	0.039993	0.213783
5	-0.002184	0.046932	1.736303	0.070744	0.040744	0.216638
6	-0.000672	0.047045	1.735061	0.070813	0.040813	0.216899
7	-0.000273	0.048522	1.719243	0.071711	0.041711	0.220277
8	-0.002277	0.04863	1.718116	0.071776	0.041776	0.220522
9	-0.001138	0.056209	1.647800	0.076311	0.046311	0.237084
10	-0.003121	0.051015	1.694205	0.073215	0.043215	0.225865
11	-0.004341	0.051712	1.687551	0.073633	0.043633	0.227402
12	-0.004218	0.04894	1.714904	0.071964	0.041964	0.221224
13	-0.001894	0.050188	1.702295	0.072717	0.042717	0.224026
14	0.000362	0.049854	1.705618	0.072516	0.042516	0.223280
15	-0.004007	0.046745	1.738370	0.070630	0.040630	0.216206
16	-0.002919	0.048028	1.724447	0.071411	0.041411	0.219153
17	-0.000766	0.04733	1.731948	0.070987	0.040987	0.217555
18	0.000343	0.054605	1.661379	0.075360	0.045360	0.233677
19	-0.002159	0.046265	1.743735	0.070337	0.040337	0.215093
20	-0.001691	0.05615	1.648288	0.076276	0.046276	0.236960
21	-0.001698	0.04956	1.708575	0.072338	0.042338	0.222621
22	-0.002416	0.050875	1.695559	0.073131	0.043131	0.225555
23	-0.000434	0.053348	1.672472	0.074612	0.044612	0.230972
24	-0.001891	0.049841	1.705748	0.072508	0.042508	0.223251
25	-0.001994	0.053521	1.670921	0.074715	0.044715	0.231346
26	-0.003276	0.052663	1.678694	0.074203	0.044203	0.229484
27	-0.000727	0.05151	1.689463	0.073512	0.043512	0.226958
28	-0.003008	0.047931	1.725479	0.071352	0.041352	0.218931
29	-0.002661	0.046884	1.736832	0.070715	0.040715	0.216527
30	-0.001345	0.054052	1.666208	0.075031	0.045031	0.232491
31	-0.003479	0.050181	1.702361	0.072713	0.042713	0.224011
32	-0.003412	0.046233	1.744096	0.070317	0.040317	0.215019
33	-0.001294	0.049603	1.708141	0.072364	0.042364	0.222717
34	-0.003333	0.055154	1.656660	0.075686	0.045686	0.234849
35	-0.001978	0.043437	1.777228	0.068599	0.038599	0.208415
36	-0.002085	0.051082	1.693559	0.073255	0.043255	0.226013
37	-0.000945	0.049516	1.709020	0.072312	0.042312	0.222522
38	0.001104	0.047377	1.731437	0.071015	0.041015	0.217663
39	-0.001602	0.046515	1.740930	0.070490	0.040490	0.215673
40	-0.002733	0.05015	1.702668	0.072694	0.042694	0.223942
441	-0.002932	0.044974	1.758612	0.069546	0.039546	0.212071

SEED	μ_Z	σ_Z^2	β	ρ_Z'	$\rho_Z' - \rho$	σ_Z
42	-0.002474	0.056458	1.645747	0.076458	0.046458	0.237609
43	-0.000713	0.053342	1.672526	0.074608	0.044608	0.230959
44	-0.003076	0.050068	1.703483	0.072645	0.042645	0.223759
45	-0.004455	0.054231	1.664637	0.075137	0.045137	0.232876
46	-0.001211	0.051773	1.686973	0.073670	0.043670	0.227537
47	-0.000271	0.052927	1.676281	0.074360	0.044360	0.230059
48	-0.000242	0.049881	1.705348	0.072532	0.042532	0.223341
49	-0.002032	0.047903	1.725778	0.071335	0.041335	0.218868
50	-0.001157	0.043841	1.772235	0.068848	0.038848	0.209382
51	-0.001919	0.048377	1.720762	0.071623	0.041623	0.219948
52	-0.001148	0.052565	1.679595	0.074144	0.044144	0.229271
53	-0.002138	0.04596	1.747190	0.070150	0.040150	0.214383
54	-0.003161	0.048161	1.723038	0.071492	0.041492	0.219456
55	-0.000983	0.04824	1.722203	0.071540	0.041540	0.219636
56	-0.000526	0.046915	1.736490	0.070734	0.040734	0.216599
57	-0.0013	0.050657	1.697680	0.073000	0.043000	0.225071
58	-0.001691	0.045047	1.757753	0.069591	0.039591	0.212243
59	-0.001583	0.046085	1.745770	0.070227	0.040227	0.214674
60	-0.002746	0.049366	1.710542	0.072221	0.042221	0.222185
61	0.001456	0.045048	1.757741	0.069591	0.039591	0.212245
62	-0.000841	0.046353	1.742745	0.070391	0.040391	0.215297
63	-0.001384	0.044670	1.762210	0.069359	0.039359	0.211353
64	-0.001951	0.045973	1.747042	0.070158	0.040158	0.214413
65	-0.001322	0.045109	1.757025	0.069629	0.039629	0.212389
66	-0.003699	0.050685	1.697406	0.073017	0.043017	0.225133
67	-0.001303	0.048213	1.722488	0.071523	0.041523	0.219575
68	-0.001605	0.046374	1.742509	0.070404	0.040404	0.215346
69	0.000724	0.045168	1.756334	0.069665	0.039665	0.212528
70	-0.001106	0.046654	1.739380	0.070575	0.040575	0.215995
71	-0.001988	0.049448	1.709709	0.072271	0.042271	0.222369
72	-0.001103	0.053124	1.674493	0.074478	0.044478	0.230486
73	-0.001845	0.047694	1.728015	0.071208	0.041208	0.218390
74	-0.004281	0.051631	1.688315	0.073585	0.043585	0.227225
75	0.000097	0.05137	1.690797	0.073428	0.043428	0.226650
76	-0.001404	0.046008	1.746644	0.070180	0.040180	0.214495
77	0.000409	0.046136	1.745192	0.070258	0.040258	0.214793
78	0.000795	0.05509	1.657206	0.075648	0.045648	0.234713
79	-0.001961	0.04623	1.744130	0.070316	0.040316	0.215012
80	-0.001209	0.051135	1.693048	0.073287	0.043287	0.226130
81	0.00094	0.054141	1.665426	0.075084	0.045084	0.232682
82	-0.003193	0.051561	1.688979	0.073543	0.043543	0.227070
83	-0.00126	0.04716	1.733801	0.070883	0.040883	0.217164
84	-0.001921	0.050052	1.703642	0.072635	0.042635	0.223723
85	-0.001164	0.046228	1.744152	0.070314	0.040314	0.215007
86	-0.003175	0.048034	1.724384	0.071415	0.041415	0.219167
87	-0.002028	0.047141	1.734009	0.070871	0.040871	0.217120
88	-0.001125	0.042341	1.791149	0.067920	0.037920	0.205769
89	-0.002331	0.045608	1.751223	0.069935	0.039935	0.213560
90	-0.000351	0.046799	1.737772	0.070663	0.040663	0.216331
91	-0.00713	0.051262	1.691830	0.073363	0.043363	0.226411
92	-0.000184	0.052027	1.684587	0.073822	0.043822	0.228094

SEED	μ_Z	σ_Z^2	β	ρ_Z'	$\rho_Z' - \rho$	σ_Z
93	0.000608	0.045932	1.747509	0.070133	0.040133	0.214318
94	-0.001275	0.047765	1.727253	0.071251	0.041251	0.218552
95	-0.001442	0.04831	1.721466	0.071582	0.041582	0.219795
96	-0.002326	0.047344	1.731795	0.070995	0.040995	0.217587
97	-0.001231	0.053624	1.670001	0.074776	0.044776	0.231569
98	-0.001099	0.051294	1.691523	0.073382	0.043382	0.226482
99	-0.002484	0.051689	1.687766	0.073619	0.043619	0.227352
100	-0.001055	0.056847	1.642569	0.076688	0.046688	0.238426
Average	-0.001690	0.048402	1.712675	0.072184	0.042184	0.221967
Standard Deviation	0.001365		0.032525	0.001944	0.001944	0.007224

<u>Calculation of a t-test statistic for Equation (5-11)</u>

$$H_0: \quad \mu_V = 0$$
$$H_A: \quad \mu_V \neq 0$$

The t-test statistic is calculated as

$$\frac{\mu_V - \mu}{\sigma} = \frac{-0.00169 - 0}{0.001365} = -1.2381 \ .$$

<u>Calculation of a likelihood ratio test statistic for Equation (5-13)</u>

$$H_0: \ \rho_V' = \rho_Z'$$
$$H_A: \ \rho_V' \neq \rho_Z'$$

The test statistic is distributed chi-square, such that

$$-2 \ln(\mathcal{L}) \approx \chi^2 \ ,$$

where

$$\mathcal{L} = \frac{1}{2} \ln(L_1) - \frac{1}{2} \ln(L_2) \ ,$$

given that L_1 is the likelihood under the restricted model, where,

$$\mu_{\rho_V'} \neq \mu_{\rho_Z'} \ ,$$

and L_2 is the likelihood under the unrestricted model,

$$\mu_{\rho_V'} = \mu_{\rho_Z'} \ .$$

REFERENCES

Albright, Louis D. and Michael B. Timmons. "Behavior of Dairy Cattle in Free Stall Housing." Transactions of the American Society of Agricultural Engineers. St. Joseph, MI: American Society of Agricultural Engineers, 1984, p. 1119-1126.

Anderson, J.R., J.L. Dillon, and J.B. Hardaker. Agricultural Decision Analysis. Ames, Iowa: Iowa State University Press, 1977.

Ando, Albert. "On the Contributions of Herbert A. Simon to Economics." Scandanavian Journal of Economics. 81,1 (1979): 83-93.

Antle, John M. "Nonstructural Risk Attitude Estimation." American Journal of Agricultural Economics. 71 (1989): 774-784.

Armstrong, Dennis. "Designs That Beat the Heat." Dairy Illustrated. 24,2 (1992): 22-26.

Barry, Peter, editor. Risk Management in Agriculture. Ames, Iowa: Iowa State University Press, 1984.

Batie, Sandra S. Soil Erosion: Crisis in America's Cropland?. Washington, D.C.: The Conservation Foundation, 1983.

Batie, Sandra S. "Agriculture as the Problem: New Agendas and New Opportunities." Southern Journal of Agricultural Economics. 20,1 (1988): 1-11.

Bernanke, Ben S. "Irreversibility, Uncertainty, and Cyclical Investment." Quarterly Journal of Economics. 98 (1983): 85-106.

Black, Fischer and Myron Scholes. "The Pricing of Options and Corporate Liabilities." Journal of Political Economy. 3 (1973): 637-654.

Blake, John, James Donald, and William Magette, editors. National Livestock, Policy and Aquaculture Waste Management: Proceedings of the National Workshop. ASAE Publication 03-92. St. Joseph, Michigan: American Society of Agricultural Engineers, 1992.

Boggess, W. G. and C.B. Amerling. "A Bioeconomic Simulation Analysis of Irrigation Investments." Southern Journal of Agricultural Economics. 15,2: (1983): 85-91.

Boggess, W.G., E.G. Flaig, and C.M. Fonyo. "Florida's Experience with Managing Nonpoint Source Phosphorus Runoff into Lake Okeechobee." In ed. C. Russell and J. Shogren. The Management of Nonpoint Source Pollution. Dordrecht, The Netherlands: Kluwer Press. 1993.

Boggess, William G., John Holt, and Robert P. Smithwick. "The Economic Impact of the Dairy Rule on Dairies in the Lake Okeechobee Drainage Basin." Food and Resource Economics Department Staff Paper, Number 91-39, University of Florida, November, 1991.

Brennan, Michael J. and Eduardo S. Schwartz. "Evaluating Natural Resource Investments." Journal of Business. 58,2 (1985): 135-157.

Brimelow, Peter and Leslie Spencer. "You Can't Get There From Here." Forbes. 6 July 1992.

Brister, Robin. "Texas Association of Dairymen Update: Celebrate Ag Week, Watch the Legislature." Stephenville (Texas) Empire-Tribune. 21 March 1993a.

Brister, Robin. "Water Quality Report On Way." Stephenville (Texas) Empire-Tribune. 18 July 1993b.

Brown, Travis. "Put a Moratorium on New Dairies in Erath County." Stephenville (Texas) Empire Tribune. 29 April 1992.

Brown, Travis. "Myths and Reality of the Dairy Industry." Stephenville (Texas) Empire Tribune. 10 March 1993.

Browner, Carol M. "Opening Statement of the Administrator Designate of the Environmental Protection Agency Before the Committee on Environment and Public Works of the United States Senate." 11 January 1993.

Burrows, Thomas M. "Pesticide Demand and Integrated Pest Management: A Limited Dependent Variable Analysis." American Journal of Agricultural Economics. 65 (1983): 806-810.

Bush, George. "Building a Better America: Statement to a Joint Session of Congress." Washington, D.C.: The White House. 9 February 1989.

Byerlee, Derek and Edith Hesse de Polanco. "Farmers' Stepwise Adoption of Technological Packages: Evidence from the Mexican Altiplano." American Journal of Agricultural Economics. 68 (1986): 519-527.

Caldwell, Bruce J. "Economic Methodology and Behavioral Economics: An Interpretive History." In B. Gilad and S. Kaish, ed. Handbook of Behavioral Economics: Volume A. Greenwich, Connecticut: JAI Press, Inc., 1986.

Carriker, Roy R. "The Federal Government and Water Pollution Control." Institute of Food and Agricultural Sciences, Water Resources Council, Number WRC-13, University of Florida. 1979.

Carriker, Roy R. "Water Quality." Food and Resource Economics Department Staff Paper, Number 93-15, University of Florida. June, 1993.

Carroll, E.J. and D.E. Jasper. "Distribution of Enterobacteriaceae in Recycled Manure Bedding on California Dairies." Journal of Dairy Science. 61 (1978): 1498-1508.

Caswell, Margriet and David Zilberman. "The Choices of Irrigation Technologies in California." American Journal of Agricultural Economics. 67 (1985): 224-234.

Caswell, Margriet and David Zilberman. "The Effects of Well Depth and Land Quality on the Choice of Irrigation Choice." American Journal of Agricultural Economics. 68 (1986): 224-234.

Cicarelli, James and Julianne Cicarelli. "Herbert Alexander Simon - 1978." In Nobel Laureates in Economic Sciences: A Biographical Dictionary. ed. Bernard S. Katz. New York, New York: Garland Publishing, 1989.

Clark, Edwin H., Jennifer A. Haverkamp, and William Chapman. Eroding Soils: The Off-Farm Impacts. Washington, D.C.: The Conservation Foundation, 1985.

Comstock, Gary, ed. Is There a Moral Obligation to Save the Family Farm?. Ames, Iowa: Iowa State University Press, 1987.

Copeland, Thomas E. and J. Fred Weston. Financial Theory and Corporate Policy. Third edition. Reading, Massachusetts: Addison-Wesley Publishing Company, 1988.

Cordell, Joe. "There's Light Ahead." Stephenville (Texas) Empire-Tribune. 31 May 1992.

Cox, John C. and Stephen A. Ross. "The Valuation of Options for Alternative Stochastic Processes." Journal of Financial Economics. 3 (1976): 145-166.

Cox, John C., Stephen A. Ross, and Mark Rubinstein. "Option Pricing: A Simplified Approach." Journal of Financial Economics. 7 (1979): 229-263.

DeJong, Donald. "Nuisance Odor Reform Dairies' Responsibility." Stephenville (Texas) Empire-Tribune. 18 April 1993a.

DeJong, Donald. "Texas Association of Dairymen: Special Report." Stephenville (Texas) Empire-Tribune. 30 May 1993b.

Dinar, Ariel and Dan Yaron. "Influence of Quality and Scarcity of Inputs on the Adoption of Modern Irrigation Technologies." Western Journal of Agricultural Economics. 15,2 (1990): 224-233.

Dixit, Avinash. "Hysteresis, Import Penetration, and Exchange Rate Pass-Through." Quarterly Journal of Economics. CIV,2 (1989): 205-228.

Dixit, Avinash. "The Art of Smooth Pasting." Unpublished manuscript, Princeton University, 27 June 1992a.

Dixit, Avinash. "Investment and Hysteresis." Journal of Economic Perspectives. 6,1 (1992b): 107-132.

Dixon, Robert. "Hybrid Corn Revisited." Econometrica. 48,6 (1980): 1451-1461.

Ervin, Christine A. and David E. Ervin. "Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence and Policy Implications." Land Economics. 58,3 (1982): 277-292.

Evans, G.B.A. and N.E. Savin. "Testing for Unit Roots: 1." Econometrica. 49,3 (1981): 753-379.

Evans, G.B.A. and N.E. Savin. "Testing for Unit Roots: 2." Econometrica. 52,5 (1984): 1241-1269.

Feder, Gershon, Richard E. Just, and David Zilberman. "Adoption of Agricultural Innovations: A Survey." Economic Development and Cultural Change. 33 (1985): 225-298.

Foster, Sam. "Program Finds Dairies Complying--Mostly." Stephenville (Texas) Empire-Tribune. 17 February 1993.

Friedman, Milton. "The Methodology of Positive Economics." In Essays in Positive Economics. Chicago, Illinois: University of Chicago Press, 1953.

Garcia, Philip, Steven T. Sonka, and Michael A. Mazzacco. "A Multivariate Logit Analysis of Farmers' Use of Financial Information." American Journal of Agricultural Economics. 65 (1983): 136-141.

Gould, Brian W., William E. Saupe, and Richard M. Klemme. "Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion." Land Economics. 65,2 (1989): 167-182.

Green, David M. Signal Detection Theory Revisited. Unpublished manuscript. Gainesville, Florida: University of Florida, Department of Psychology, January, 1992.

Green, David M. and John A. Swets. Signal Detection and Psychophysics. Los Altos, California: Peninsula Press, 1966.

Grilliches, Zvi. "Hybrid Corn: An Exploration in the Economics of Technological Change." Econometrica. 25,4 (1957): 501-522.

Gunsalus, Boyd, Eric G. Flaig, and Gary Ritter. "Effectiveness of Agricultural Best Management Practices Implemented in the Taylor Creek/Nubbin Slough Watershed and the Lower Kissimmee River Basin." In Ten Years of Controlling Agricultural Nonpoint Pollution: The RCWP Experience. ed. U.S. Environmental Protection Agency, Office of Research and Development, Office of Water. EPA Seminar Publication, The National Rural Clean Water Program Symposium, EPA/625/R-92/006. Washington, D.C.: August, 1992.

Hall, David W. and Dennis W. Risser. "Effects of Nutrient Management on Nitrogen Flux through a Karst Aquifer, Conestoga River Headwaters, Pennsylvania." In Ten Years of Controlling Agricultural Nonpoint Pollution: The RCWP Experience. ed. U.S. Environmental Protection Agency, Office of Research and Development, Office of Water. EPA Seminar Publication, The National Rural Clean Water Program Symposium, EPA/625/R-92/006. Washington, D.C.: August, 1992.

Hallady, Dennis. "Comparing Costs." The Dairyman. 73,10 (1992a): 56-57.

Hallady, Dennis. "What's New at New Dairies?" The Dairyman. 73,11 (1992b): 26.

Heiner, Ronald A. "The Origin of Predictable Behavior." American Economic Review. 73 (1983): 560-595.

Heiner, Ronald A. "Uncertainty, Signal Detection Experiments and Modeling Behavior." In Economics as a Process: The New Institutional Economics, ed. R. Langlois. New York, New York: Cambridge University Press, 1985.

Heiner, Ronald A. "The Necessity of Imperfect Decisions." Journal of Economic Behavior and Organization. 10 (1988): 29-55.

Hosemann, John K. "Economic Issues for Farmers in the Rewrite of the Clean Wate Act." Presented at the "Clean Water and the American Economy." Conference sponsored by U.S. Environmental Protection Agency and Resources for the Future, Arlington, Virginia: October, 1992.

Hull, John. Options, Futures, and Other Derivative Securities. Englewood Cliffs, NJ: Prentice-Hall, 1989.

Kalaitzandonakes, N.G. and W.G. Boggess. "A Dynamic Decision-Theoretic Model of Technology Adoption for the Competitive Firm." Technological Forecasting and Social Change: An International Journal. Fortcoming, 1993.

Koerkle, Edward H. "Effects of Nutrient Management on Surface Water Quality in a Small Watershed in Pennsylvania." In Ten Years of Controlling Agricultural Nonpoint Pollution: The RCWP Experience. ed. U.S. Environmental Protection Agency, Office of Research and Development, Office of Water. EPA Seminar Publication, The National Rural Clean Water Program Symposium, EPA/625/R-92/006. Washington, D.C.: August, 1992.

Kovan, Jessica T., Amy K. Purvis, Vernon L. Sorenson, and Lawrence L. Libby. "Linking Farm Policy and Conservation Policy: A Guide to the Conservation Provisions of the 1985 Food Security Act." Michigan State University Extension Bulletin E-2077. August, 1987.

Kraph, Eric. "Dairy Industry Paces County Ag." Stephenville (Texas) Empire-Tribune. 26 July 1992a.

Kraph, Eric. "Nuisance Odor Panel Off to Good Start, Dairy Representatives Say." Stephenville (Texas) Empire-Tribune. 25 December 1992b.

Landy, Marc K., Marc J. Roberts, and Stephen R. Thomas. The Environmental Protection Agency: Asking the Wrong Questions. New York, New York: Oxford University Press, 1990.

Leatham, David J., John F. Schmucker, Ronald D. Lacewell, Robert D. Schwart, Ashley C. Lovell, and Greg Allen. "Impact of Texas Water Quality Laws on Dairy Income and Viability." Journal of Dairy Science. 75 (1992): 2846-2856.

Libby, Lawrence W. and William G. Boggess. "Agriculture and Water Quality: Where Are We and Why?" In Agriculture and Water Quality: International Perspectives. ed., John B. Braden and Stephen B. Lovejoy. Boulder, Colorado: Lynne Rienner Publisher, 1990.

Lichtenberg, Erik. "Land Quality, Irrigation Development, and Cropping Patterns in the Northern High Plains." American Journal of Agricultural Economics. 71 (1989): 187-194.

Lockerwetz, William. "What Have We Learned About Who Conserves Soil?" Journal of Soil and Water Conservation. 45,5 (1990): 517-523.

Lovell, Ashley, Bud Schwart, Ron Lacewell, John Schmucker, David Leatham, James Richardson, and Greg Allen. "Is There Financial Life After Mandatory Dairy Waste Systems?" The Dairyman. 73,12 (1992): 22-25.

Maddala, G.S. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge, England: Cambridge University Press, 1983.

Malik, Arun S., Bruce A. Larson, and Marc Ribaudo. "Agricultural Nonpoint Source Pollution and Economic Incentive Policies: Issues in the Reauthorization of the Clean Water Act." U.S. Department of Agriculture, Economic Research Service, Resources and Technology Division, Staff Report AGES-9229, November, 1992.

Mason, Scott P. and Robert C. Merton. "The Role of Contingent Claims Analysis in Corporate Finance," In Recent Advances in Corporate Finance, ed. Edward I. Altman and Marti G. Subrahmanyam. Homewood, Illinois: Richard D. Irwin, Publisher, 1985.

Matulich, Scott C., Hoy F. Carman, and Harold O. Carter. "Cost-Size Relationships for Large-Scale Dairies with Emphasis on Waste Management." California Agricultural Experiment Station, Giannini Foundation Research Report Number 324, October, 1977.

McConnell, Campbell R. and Stanley L. Brue. Economics: Principles, Problems and Policies. Eleventh edition. New York, New York: McGraw-Hill Publishing Company, 1990.

McDonald, Robert, and Daniel R. Siegel. "The Value of Waiting to Invest." Quarterly Journal of Economics. 101 (1986): 707-728.

McFarland, Dan F. "Well-bedded free stalls are well-used free stalls." Hoard's Dairyman. 25 August 1992, p. 570.

Meals, Donald W. "Relating Land Use and Water Quality in the St. Albans Bay Watershed, Vermont." In Ten Years of Controlling Agricultural Nonpoint Pollution: The RCWP Experience. ed. U.S. Environmental Protection Agency, Office of Research and Development, Office of Water. EPA Seminar Publication, The National Rural Clean Water Program Symposium, EPA/625/R-92/006. Washington, D.C.: August, 1992.

Moore, James. "Dairy Manure Solid Separation." In Dairy Manure Management. Ithaca, NY: Northeastern Regional Engineering Service, Cooperative Extension Report #NRAES-31, February, 1989.

Moore, J.A., R. Pederson, and J. Worledge. "Keeping Bacteria Out of the Bay." In Ten Years of Controlling Agricultural Nonpoint Pollution: The RCWP Experience. ed. U.S. Environmental Protection Agency, Office of Research and Development, Office of Water. EPA Seminar Publication, The National Rural Clean Water Program Symposium, EPA/625/R-92/006. Washington, D.C.: August, 1992.

Moss, Charles B., Allen M. Featherstone, and Timothy G. Baker. "Agricultural Assets in an Efficient Multiperiod Investment Portfolio." Agricultural Finance Review. 47 (1987): 82-93.

"National Pollution Discharge Elimination System General Permit and Reporting Requirements for Discharges from Concentrated Animal Feeding Operations; Notice of Draft General NPDES Permits for Discharges from Confined Animal Feeding Operations." Federal Register. 57,141 (22 July 1992): 32475-32499.

"National Pollution Discharge Elimination System General Permit and Reporting Requirements for Discharges from Concentrated Animal Feeding Operations; Notice." Federal Register. 58,24 (8 February 1993): 7610-7644.

Norris, Patricia E. and Sandra S. Batie. "Virginia Farmers' Soil Conservation Decisions: An Application of Tobit Analysis." Southern Journal of Agricultural Economics. 19,1 (1987): 79-90.

"Of Butterflies and Condors." The Economist. 16 February 1991, p. 58-59.

Office of Technology Assessment, Congress of the United States. Beneath the Bottom Line: Agricultural Approaches to Reduce Agrichemical Contamination of Groundwater. OTA-F-418. Washington, D.C.: U.S. Government Printing Office, November, 1990.

Office of Technology Assessment, Congress of the United States. U.S. Dairy at a Crossroad: Biotechnology and Policy Choices--Special Report. OTA-F-470. Washington, D.C.: U.S. Government Printing Office, May, 1991.

Outlaw, Joe L., Robert B. Schwart, Jr., Ronald D. Knutson, Amy P. Pagano, Allen Gray, and John Miller. "Impacts of Dairy Waste Management Regulations." Agricultural Food Policy Center Working Paper, Number 93-4, Texas A & M University, May, 1993.

Pagano, Amy Purvis, Kristin A. Gill, and Heather Haedge Jones. "Design and Management of Free Stall Housing: An Overview." Texas Institute for Applied Environmental Research, Institute Information Bulletin 92-1, October, 1992a.

Pagano, Amy Purvis, Kristin A. Gill, and Heather Haedge Jones. "Free Stall Dairy Design and Management: Visits to Six Texas Dairies." Texas Institute for Applied Environmental Research, Institute Information Bulletin 92-2, November, 1992b.

Pagano, Amy Purvis, Heather Haedge Jones and Kristin A. Gill. "Free Stall Dairy Design and Management: A Visit to California's Central Valley." Texas Institute for Applied Environmental Research, Institute Information Bulletin 92-3, November, 1992c.

Pagano, Amy Purvis, Kristin A. Gill, and Heather Haedge Jones. "Free Stall Dairy Design and Management: Visits with Three Florida Producers." Texas Institute for Applied Environmental Research, Institute Information Bulletin 93-1, January, 1993a.

Pagano, Amy Purvis, John Holt, Robert B. Schwart and William G. Boggess."A Profile of Estimated Costs and Returns Associated with Free Stall Dairying in Central Texas." Food and Resource Economics Department Staff Paper, Number 93-13, University of Florida. May, 1993b.

Palisade Corporation. "@RISK Risk Analysis and Simulation Add-In for Lotus 1-2-3: A Software Package." Version 2.01. Newfield, NY, 6 February 1992.

Phipps, Tim T. and Pierre R. Crosson. "Agriculture and the Environment: An Overview." In Agriculture and the Environment. ed. Tim T. Phipps, Pierre R. Crosson, and Kent A. Price. Washington, DC: Resources for the Future, 1986.

Pindyck, Robert S. "Irreversibility and the Explanation of Investment Behavior." In Stochastic Models and Option Values, ed. D. Lund and B. Oksendal. North-Holland: Elsevier Science Publishers, 1991a.

Pindyck, Robert S. "Irreversibility, Uncertainty, and Investment." Journal of Economic Literature. 29 (1991b): 1110-1152.

Pindyck, Robert S. "Investments of Uncertain Cost." International Center for Research on Management of Technology. Working Paper #71-92, Massachusetts Institute of Technology, September, 1992.

Porterfield, Jim. "American Farm Bureau Federation Shares Perspective on Lessons Learned from the National Rural Clean Water Program." EPA NPS News-Notes. EPA-841-N-93-006. 28 (April, 1993): 21-23.

Purvis, Amy Kathleen. "An Economic Analysis of Landowners' Willingness to Enroll Filter Strips in a Conservation Program: A Case Study in Newaygo County, Michigan." Master's Thesis, Michigan State University, Department of Agricultural Economics, 1989a.

Purvis, Amy, John P. Hoehn, Vernon L. Sorenson, and Francis J. Pierce. "Farmers' Response to a Filter Strip Program: Results from a Contingent Valuation Study." Journal of Soil and Water Conservation. 44,5 (1989b): 501-504.

Rahm, Michael R. and Wallace E. Huffman. "The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables." American Journal of Agricultural Economics. 66 (1984): 405-413.

Reichelderfer, Katherine and William G. Boggess. "Government Decision Making and Program Performance: The Case of the Conservation Reserve Program." American Journal of Agricultural Economics. 70,1 (1988): 1-11.

Rogers, E.M. and P.C. Thomas. Bibliography on the Diffusion of Innovations. Ann Arbor: Department of Population Planning, University of Michigan, 1975. Cited in Everett M. Rogers. "New Product Adoption and Diffusion." Journal of Consumer Research. 2 (1976): 290-301.

Rook, Sarah P. and Gerald A. Carlson. "Participation in Pest Management Groups." American Journal of Agricultural Economics. 67 (1985): 563-566.

Ross, Stephen. Quoted in The Economist. 16 February 1991, 58-59, "Of Butterflies and Condors."

Rubinstein, Mark. "Derivative Asset Analysis." Journal of Economic Perspectives. 1,2 (1987): 73-83.

Rynk, Robert. "Composting as a Dairy Manure Management Technique." In Dairy Manure Management. Ithaca, NY: Northeastern Regional Engineering Service, Cooperative Extension Report #NRAES-31, February, 1989.

Schlagel, Joel D. "Spatial and Temporal Change in Animal Waste Application in the Jewett Brook Watershed, Vermont, 1983-1990." In Ten Years of Controlling Agricultural Nonpoint Pollution: The RCWP Experience. ed. U.S. Environmental Protection Agency, Office of Research and Development, Office of Water. EPA Seminar Publication, The National Rural Clean Water Program Symposium, EPA/625/R-92/006. Washington, D.C.: August, 1992.

Schwart, Robert B., Jr. and Ronald D. Lacewell. "Dairy Waste Management Estimator Worksheet" and LAGOON software. Texas Agricultural Experiment Station, Texas Agricultural Extension Service, Department of Agricultural Economics, Texas A & M University, May, 1992.

Schultz, Theodore W. "The Value of the Ability to Deal with Disequilibria." Journal of Economic Literature. 13 (1975): 827-846.

Simon, Herbert A. "A Behavioral Model of Rational Choice." Quarterly Journal of Economics. 69 (1955): 99-118.

Simon, Herbert A. "Rational Choice and the Structure of the Environment." Psychological Review. 63,2 (1956): 129-138.

Simon, Herbert A., "Theories of Decision-Making in Economics and Behavioral Science," American Economic Review, 49,3 (1959): 253-283.

Simon, Herbert A. "Rationality as Process and as Product of Thought." American Economic Review. 68 (1978): 1-16.

Simon, Herbert A. "Rational Decision Making in Business Organizations." American Economic Review. 69,4 (1979): 493-513.

Simon, Herbert A. "The Failure of Armchair Economics." Challenge. November-December, 1986, p. 18-25.

Simon, Herbert A. "The Scientist as Problem Solver." In Complex Information Processing: The Impact of Herbert A. Simon. ed. David Klahr and Kenneth Kotovsky. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc., 1989a.

Simon, Herbert A. "The State of Economic Science." In The State of Economic Science: Views of Six Nobel Laureates. ed., Werner Sichel. Kalamazoo, Michigan: Upjohn Institute, 1989b.

Sims, Cathey Yarbrough. "Not All Agriculture Folks Support 'Odor' Bills." Stephenville (Texas) Empire-Tribune. 18 May 1993.

Smith, V. Kerry and F. Reed Johnson. "How Do Risk Perceptions Respond to Information? The Case of Radon." The Review of Economics and Statistics. 70,1 (1988a): 1-8.

Smith, V. Kerry, William H. Desvousges, Ann Fisher, and F. Reed Johnson. "Learning About Radon's Risk," Journal of Risk and Uncertainty, 1 (1988b): 233-258.

Smith, V. Kerry and William H. Desvousges. "Risk Communication and the Value of Information: Radon as a Case Study." The Review of Economics and Statistics. 72 (1990): 137-142.

Stalcup, Larry. "Big Stink in Texas." Dairy Today. August, 1992, p. 14-16.

Strange, Marty. Family Farming. Lincoln, Nebraska: University of Nebraska, 1988.

Summers, Lawrence H. "Investment Incentives and the Discounting of Depreciation Allowances." In The Effects of Taxation on Capital Accumulation. ed. Martin Feldstein. Chicago: University of Chicago Press, 1987. Cited in Avinash Dixit. "Investment and Hysteresis." Journal of Economic Perspectives. 6,1 (1992b): 107-132.

Sweeten, John, James C. Barker, and John P. Burt. "Dairy Manure Management Systems for Southern Climates." In Dairy Housing II: Proceedings of the Second National Dairy Housing Conference. St. Joseph, MI: American Society of Agricultural Engineers, 1983, p. 54-61.

Terrell, Gaynell. "Activists Claim Animal Waste Pollutes River." The Houston Post. 18 October 1992.

Texas Milk Market Administrator. Texas Milk Market Report. Carrollton, Texas: Office of the Market Administrator, Federal Order 126. January, 1990 - June, 1993.

U.S. Department of Agriculture, National Agricultural Statistics Service. Agricultural Statistics. Washington, D.C.: U.S. Government Printing Office, 1992.

U.S. Department of Agriculture. "Water Quality Program Plan to Support the President's Water Quality Initiative." Official Policy Statement. Washington, D.C.: Office of the Deputy Secrtetary of Agriculture, July, 1989.

U.S. Department of Commerce, Bureau of Census. Census of Agriculture. 1934 - 1987.

U.S. Environmental Protection Agency, Office of Water. Managing Nonpoint Source Pollution: Final Report to Congress on Section 319 of the Clean Water Act (1989). EPA-506/9-90. Washington, D.C.: January, 1992a.

U.S. Environmental Protection Agency, Office of Research and Development, Office of Water. Ten Years of Controlling Agricultural Nonpoint Pollution: The RCWP Experience. EPA Seminar Publication, The National Rural Clean Water Program Symposium, EPA/625/R-92/006. Washington, D.C.: August, 1992b.

Varian, Hal R. "The Arbitrage Principle in Financial Economics." Journal of Economic Perspectives. 1,2 (1987): 55-72.

White, Halbert. Asymptotic Theory for Econometricians. Orlando, Florida: The Academic Press, Inc., 1983.

Whittlesey, Norman K. and Roy R. Carriker. "Water, Agriculture and Public Policy." In Food and Agricultural Policy Issues and Choices for 1995. ed. M.C Hallberg, R.G.F. Spitze, and D.E. Ray. Boulder, Colorado: Westview Press, Forthcoming, 1993.

BIOGRAPHICAL SKETCH

Amy Kathleen Purvis was born in Fort Collins, Colorado, and raised in Fremont, Michigan. She graduated cum laude from Fremont High School in 1978. She attended Hope College in Holland, Michigan, graduating magna cum laude with a Bachelor of Arts degree in history in May, 1982.

She joined the Peace Corps in September, 1982. She learned aquaculture at the University of Oklahoma and then studied French and Tshiluba at the Centre de Formation in Bukavu, Zaire. She served as a fisheries extension agent and then as a Peace Corps volunteer leader from February, 1983 to March, 1986. She speaks French, Kiswahili and Tshiluba.

Amy started graduate school in June, 1986. She earned a Master of Science degree in agricultural economics in June, 1989. Her thesis was entitled "An Economic Analysis of Landowners' Willingness to Enroll Filter Strips in a Conservation Program: A Case Study in Newaygo, Michigan."

Amy entered the Ph.D. program at the University of Florida in the Food and Resource Economics Department in May, 1989. She was admitted to Ph.D. candidacy in April, 1992. She worked as a summer intern at the Economic Research Service in Washington, D.C. from May to August, 1990. She worked as a research

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I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

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